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# Military Operations Research

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# Executive Summaries

## CONSTRAINED SYSTEM OPTIMIZATION AND CAPABILITY BASED ANALYSIS

*by R. Garrison Harvey, Kenneth W. Bauer Jr. and Joseph R. Litko*

In recent years, military analysts have witnessed the increasing use of response surface methods as applied to analysis of large-scale simulation models. Typically, the output of such an analysis is a stochastic response surface. Often this surface is used for subsequent study, perhaps as an objective function in an optimization problem. This paper presents an alternative to the traditional approaches to optimizing a stochastic response surface subject to constraints. It also presents an extension that offers a new way of quickly visualizing complex relationships among variables in a system. First, the paper focuses on the stochastic nature of the response surface and the implications for subsequent optimization and sensitivity analysis. Next, we present a three step process to evaluate and optimize complex systems. Finally, we present a current application: a unique interactive computer model called Capability Based Analysis (CBA).

## ARDENNES CAMPAIGN SIMULATION (ARCAS)

*by Walter J. Bauman*

The Ardennes Campaign Simulation (ARCAS) study was performed to improve the credibility of the Stochastic Concepts Evaluation Model (STOCEM), a theater-level combat simulation, by comparing the outcome of a STOCEM simulation of the World War II (WW II) Ardennes campaign of 1944–45 (also known as the Battle of the Bulge) with historical campaign results.

Historical campaign data had been developed, using archival sources, into a computerized data base denoted as the Ardennes Campaign Simulation Data Base (ACSDB). The initial positions, configuration, strengths, compositions and availability of forces for the campaign, as depicted in the ACSDB, are used to define the STOCEM force laydown. Representative simulation results (front line movement, major system losses, and personnel casualties) are compared with historical results from the ACSDB. Stochastic variability of model results is also quantified in terms of confidence limits about each sample mean and bounds on sample outcomes. The comparison of simulation results with history is used to develop guidelines for investigating algorithmic changes which may improve model credibility of the STOCEM. Insights on model verification and validation (V & V) are also developed.

Study results indicate that ARCAS STOCEM tends to generate more force movement, weapon system losses, and personnel casualties than occurred in history. Investigations of potential changes to STOCEM logic/inputs suggested by the simulation/history comparisons include simulation of a "breakthrough" attack posture, moderation of attacker move rate in response to a sustained rapid combat advance, and reduction of base lethality against armor for an attacker possessing a high strength advantage.

## FINDING AN OPTIMAL STATIONING POLICY FOR THE US ARMY IN EUROPE AFTER THE FORCE DRAWDOWN

*by Andrew G. Loerch, Natashia Boland, Ellis L. Johnson and George L. Nemhauser*

During the Cold War, the United States Army maintained a force of two corps, about 225,000 soldiers, in Europe to deter aggression by the Soviet Union. Following the implementation of the Conventional Armed Forces Europe (CFE) Agreement in 1990 and the dissolution of the Soviet Union in 1991, the force in Europe was gradually reduced to 65,000. In a cooperative effort between analysts at the US Army Concepts Analysis Agency and those at the Computational Optimization Center at the Georgia Tech, Andy Loerch, Natashia Boland, Ellis Johnson, and George Nemhauser developed a large-scale binary integer programming model to assign the US Army units remaining in Europe to installations in an economical manner, and to make recommendations regarding which installations should be candidates for deactivation and closure.

## CONSOLIDATING THE USAF'S CONVENTIONAL MUNITIONS MODELS

*by Major Kirk A. Yost*

Starting in 1990, the USAF's shrinking budgets caused increased competition for

procurement dollars for stocks of conventional munitions. This situation also increased scrutiny of the models used to compute requirements for conventional munitions. Unfortunately, at that time the USAF was supporting four different optimization models to accomplish this job, with the predictable result that different organizations using different models were generating different requirements. In 1995, three of the four models were consolidated into one optimization system, with the aims of using the best ideas in the existing models leveraging investment in common databases, and providing a common baseline for munitions analyses in the USAF. This paper documents the formulation and development of the new Conventional Forces Assessment Model (CFAM) from both a functional and analytical point of view. More importantly, this paper shows it is both analytically and organizationally possible to consolidate existing models and reduce the support requirements while giving the users a better analysis tool.

## SATISFYING ADVANCED DEGREE REQUIREMENTS FOR U.S. AIR FORCE OFFICERS

*by Dennis C. Dietz*

In the aftemath of the Cold War, the Air Force has undergone significant organizational changes and force reductions. These actions motivated a major re-engineering study of graduate education operations the Air Force Institute of Technology (AFIT). Lt Col Dietz describes an analytical model that was developed to determine the minimum number of officers that must enter MS or PhD programs each year in order to consistently satisfy all personnel requirements (by academic specialty, degree level, and grade) at minimum cost. The model is formulated as a Markov decision process and solved using linear programming. The model results formed the basis for a specific plan to modify the AFIT personnel structure. Annual cost savings of at least $2.4 million are anticipated.

# Constrained System Optimization and Capability Based Analysis

**R. Garrison Harvey**

*William E. Wecker and Associates*

**Kenneth W. Bauer Jr.**

*Air Force Institute of Technology*

**Joseph R. Litko**

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*APPLICATION AREA:*
Resource Analysis and Forecast

*OR METHODOLOGY:*
Linear Programming, Response Surface Methodology

## Abstract

In recent years, military analysts have witnessed the increasing use of response surface methods as applied to analysis of large-scale simulation models. Typically, the output of such an analysis is a stochastic response surface. Often this surface is used for subsequent study, perhaps as an objective function in an optimization problem. This paper presents an alternative to the traditional approaches to optimizing a stochastic response surface subject to constraints. It also presents an extension that offers a new way of quickly visualizing complex relationships among variables in a system. First, the paper focuses on the stochastic nature of the response surface and the implications for subsequent optimization and sensitivity analysis. Next, we present a three step process to evaluate and optimize complex systems. Finally, we present a current application: a unique interactive computer model called Capability Based Analysis (CBA).

## INTRODUCTION

Consider the problem of allocating a fixed budget to purchasing a mixed fleet of aircraft such as the Air Mobility Command (AMC) heavy transports: the C-5, C-17, C-141, and commercial derivatives. Each aircraft has different characteristics (e.g., material handling requirements, crew size, parking space, speed, payload/range curve, acquisition and support costs). In addition to aircraft characteristics, parameters like maximum aircraft on the ground (MOG) at all airfields, cargo type, cargo delivery schedule, and utilization rates influence the effectiveness of the heavy transport fleet. Given these aircraft characteristics and parameters, we seek an optimal mix of aircraft to maximize throughput in an armed conflict.

Suppose a simulation model is used to derive a response surface of throughput as a function of the aircraft characteristics and system parameters mentioned above. An LP model might then be used to explore strategies which maximize throughput, or say balance throughput versus risk. The LP would include many of the physical constraints in the simulation perhaps adding budgetary considerations if the purpose of the analysis is strategic planning rather than execution. Naive analysis treats the response surface as a deterministic function missing the fact that the objective function coefficients are random variables derived from the simulation. The focus of this research is in developing a better approach to handling the stochastic nature of these coefficients.

This paper is organized as follows. First, we present some background to the problem. Next, we discuss the impact of the stochastic nature of the response surface in a constrained optimization problem. We follow this discussion with the development of a three step process to identify the true optimum point and identify a robust solution. In step one experimental design is used to estimate the response surface and covariance matrix. Step two samples the objective function of the mathematical program (i.e., response surface) and identifies the associated extreme points. Finally, step three presents a method to identify the optimal extreme point and present that information to a decision maker. We conclude the paper with an extension of this basic research and show some practical results. This research is an extension of that seen in Harvey et al. (1992).

## BACKGROUND

Biles and Swain (1977) present several strategies for constrained simulation optimization. They fit and validate a response surface using an n-dimensional simplex, biradial, or equiradial design. They account for the variance of the error term, but assume the "response surfaces are the expected values of the observed responses". They do not directly account for the stochastic nature of the response surface, but use an iterative method of applying an optimization procedure and then returning to the simulation model until stopping criteria are met. Their procedures include direct search techniques, as well as first-order and second-order response surface methodology.

Myers (1989) concludes that, "Many users of RSM allow conclusions to be drawn concerning the nature of a response surface and the location of optimal response without taking into account the distributional properties of the estimated attributes of the underlying response surface."

Morben (1987), in solving a "real world" problem, illustrates a case where using the expected value of a stochastic objective function leads to an answer that falls outside a 95% confidence bound found through a Monte Carlo analysis. This case

clearly demonstrates there is a risk in some situations of using only the expected value of a response surface for optimization applications, and makes the case for incorporating some form of stochastic analysis.

## IMPACT OF ESTIMATION ERRORS

Figure 1(a) is a simple flow diagram of a typical analysis situation. A simulation model has been analyzed across an experimental design (or series of designs). One output of such an analysis is a stochastic response surface. The response surface acts as an approximation to the underlying simulation model. This surface is characterized by its estimated coefficients and their associated covariance matrix, Cov $(\hat{\beta})$. The response, $\hat{Y}$ is approximated as $\hat{\beta}^T\mathbf{x}$, where $\hat{\beta}$ are the regression coefficients and $\mathbf{x}$ is a vector of decision variables. Often, this response surface is used in subsequent analysis. We will consider the situation in which the surface is used as the objective function in an optimization problem. In this section we identify the problems that arise from this approach to the problem.

In the basic research, we view the simulation as a black box that consists of a "Truth Model" plus noise. Simulation output from a designed experiment allows us to estimate a response surface that becomes the objective function of a linear program and is later used in

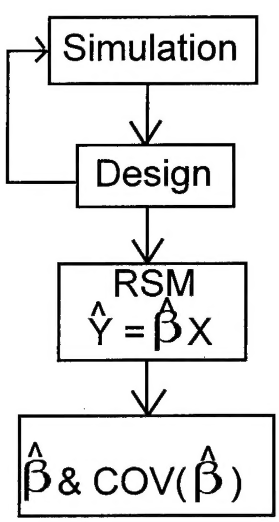



**Figure (1a).** Typical Analysis Situation.

Capability Based Analysis (CBA). The functions:

$$z^* = \mathrm{LP}(\mathbf{c}, \mathbf{A}, \mathbf{b}) \quad (1)$$

$$\hat{z}^* = \mathrm{LP}(\hat{\mathbf{c}}, \mathbf{A}, \mathbf{B}) \quad (2)$$

define the optimal value $z^*$ (or estimated optimal value $\hat{z}^*$) of a linear program. Where

$z^*$ = $\mathbf{c}^T\mathbf{x}$ true (or known) objective function
$\hat{z}^*$ = $\hat{\mathbf{c}}^T\mathbf{x}$ estimated objective function
$\mathbf{x}$ = $(x_1, x_2, \ldots, x_p)^T$ = vector of decision variables
$\mathbf{A}$ = constraint matrix
$\mathbf{b}$ = right hand side vector.
$\mathbf{c}$ = true surface coefficients underlying the metamodel
$\hat{\mathbf{c}}$ = $\mathbf{c} + \boldsymbol{\epsilon}$ estimated coefficients of objective function (response surface), with $\boldsymbol{\epsilon} \sim N(0, \sigma^2(X^TX)^{-1})$
$X$ = design matrix used to estimate the response surface

Since we assume there is no bias in the estimation of $\mathbf{c}$ we can obtain $z^*$ (the true optimum) if we evaluate the LP with the expected value of the objective function coefficients:

$$z^* = \mathrm{LP}(\mathrm{E}(\hat{\mathbf{c}}, \mathbf{A}, \mathbf{b})). \quad (3)$$

In general, $z^*$ is not equal to the expected value of the linear program with respect to the objective function coefficients. That is,

$$z^* = \mathrm{LP}(\mathbf{c}, \mathbf{A}, \mathbf{b})$$
$$= \mathrm{LP}(\mathrm{E}(\hat{\mathbf{c}}, \mathbf{A}, \mathbf{b})) \neq E(LP(\mathbf{c}, \mathbf{A}, \mathbf{b})) = \mathrm{E}(\hat{z}^*), \quad (4)$$

because the objective function of a linear programming maximization problem is a piecewise linear convex function of the objective function coefficients, $\mathbf{c}$. Looking at this in one dimension for simplicity, as in Figure 2, consider z as a function of the coefficient $c_i$. The slope of each piece-wise linear segment, $\alpha_k$, is simply the value of the decision variable $x_i$ in the basis that applies in region k. As the curve indicates, smaller values of $c_i$ tend to be accompanied by smaller slopes (i.e., the variable $x_i$ is basic at a lower value, if it is basic at all). If $c_i$ is small enough the ith variable becomes nonbasic and further reductions in $c_i$ have no effect. So

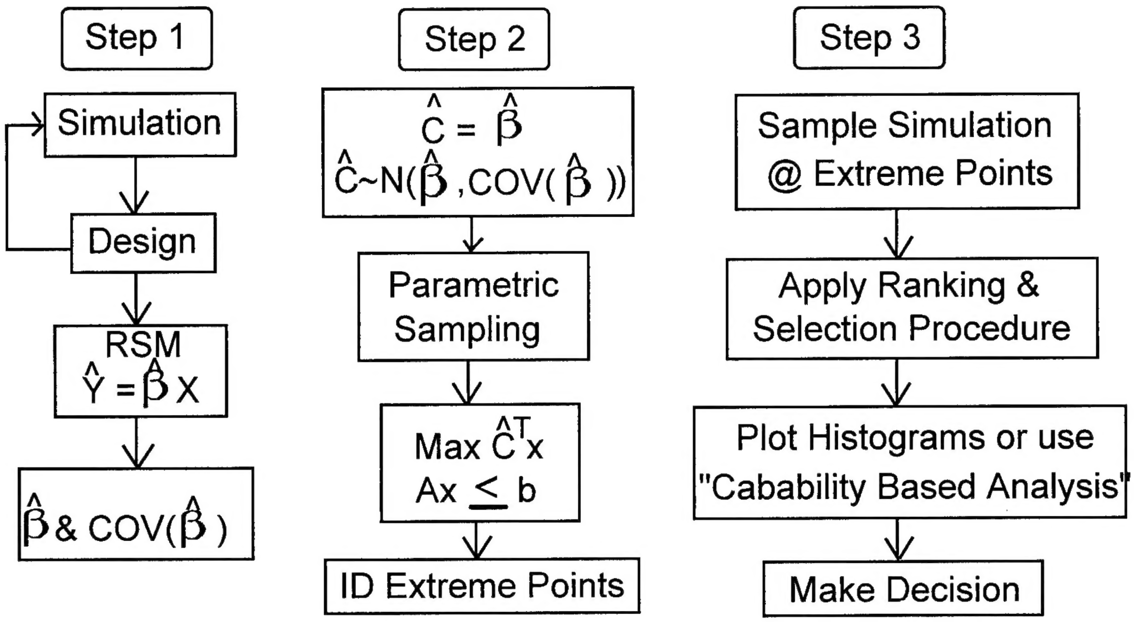



**Figure (1b). Three Step Approach.**

too, increasing $c_i$ eventually loses its effect when $x_i$ can be increased no further.

Assume the true value of objective function coefficient $c_i$, call it $c_{ik}$, lies in the $k^{th}$ piece-wise linear interval. Then,

for $c_i \geq c_{ik}$ we have $z(c_i) \geq \alpha_k c_i + z(0)$

for $c_i \leq c_{ik}$ we have $z(c_i) \geq \alpha_k c_i + z(0)$

due to the convexity of z with respect to $c_i$. Here, z(0) is the solution of the linear program when $c_i = 0$. Therefore, $E(z(c_i)) \geq E(\alpha_k c_i + z(0)) = z(E(c_i)) = z(c_{ik})$, illustrates the point made in equation 4. Figure 2 also illustrates the point that the bias in the estimated value of the objective function is proportional to the variance in the coefficients. By definition, tight distributions will seldom produce estimates that cross into adjacent piece-wise linear segments. The opposite is true of wildly varying estimates of the objective function coefficients.

With these observations in mind, we performed experiments to illustrate the bias identified in Equation 4. The computer program samples from a "Truth Model" with noise, estimates a response surface, and then uses it as the objective function of the linear program. Next the LP is solved for the estimated optimal value and the estimated optimal extreme point. We compared these values to the true optimal extreme point and its objective function value.

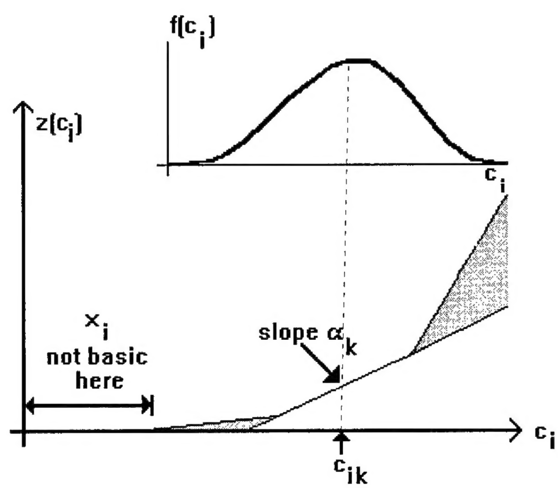



**Figure 2. Noise Impact & Bias.**

All the linear programming problems analyzed in this research exhibited positive or zero bias in the mean of the estimated optimum value of the objective function. In our experiments, the bias

$$\text{Bias} = E(\hat{z}^*) - z^* \tag{5}$$

is defined as the difference between the mean estimated optimum and the true optimum. For a given problem, both the bias and the standard error in the estimated optimum increased as the noise level increased. Figures 3 and 4 illustrate a typical case where the standard error refers to the standard error of the objective function coefficients and the sample size is 1000.

The bias increases as the standard error increases. With a true optimum of $z^* = 200$, a bias of 20 equates to a 10% error and a bias of 40 to a 20% error. The standard deviation of $\hat{z}^*$ follows a similar trend as shown in the Figure 4.

Hence, one can expect as the standard error of the parameter estimates increases both the bias and the variance of $\hat{z}^*$ increases.

Figures 5 and 6 offer a different view of the problem. In these figures we plot the objective function values on the vertical axis for 8000 samples of the objective function coefficients. For each extreme point, the objective function values are plotted in descending order.

The form of the curves in figures 5 and 6 has an intuitive explanation. Given an extreme point (i.e. fixed values of the decision variables, $x_i$'s) chosen as optimal for a sample of **c**,

$$\hat{z}^* = \hat{c}_1 x_1 + \hat{c}_2 x_2 + \hat{c}_3 x_3 + \cdots + \hat{c}_n x_n \quad (6)$$

derives its distribution from the $\hat{c}_i$. The $\hat{c}_i$ in (6) are not normally distributed since they represent a sample from $\hat{c}_i$ restricted to a range of values. But their distribution is unimodal and rough Central Limit arguments suggest $\hat{c}_i$ is approximately normal. The exact form of the distribution is not crucial however.

Note that even in choosing an incorrect extreme point (and hence, an inferior strategy), $\hat{z}^*$ can be much higher than even the true optimal extreme point $z^*$. When the standard error of the regression coefficients ($\sigma$) equals 2.25 (as in Figure 5), visits to the true optimal extreme point occur about 14% of the time, and about 98% of the solutions are "close" (not the optimal extreme point but the second or third best extreme point) the true optimal extreme point. That is, the leftmost region in Figure 5 corresponds to the true optimal extreme point and represents about 14% of the length of the "x" axis – 14% of the samples. When $\sigma = 3.25$ (as in Figure 6) visits to the true optimal extreme point occur about 7% of the time, and about 92% of the solutions are "close" to the true optimal extreme point.

When $\sigma = 4.25$ (figure not shown) visits to the true optimal extreme point occur about 6% of the time, and about 90% of the solutions are "close" to the true optimal extreme point.

Two principal difficulties arise when using estimated response surfaces as objective functions in linear programs: the bias in the estimate of the optimal value, which can dramatically mislead the decision maker, and the difficulty in identifying the correct or optimal strategy (extreme point). In the next section, we introduce a three step method for dealing with these difficulties.

# THREE STEP METHODOLOGY

## Overview

In this section we develop a three step process for the use of stochastic response surfaces as objective functions in linear programs. Figure 1(b) shows the overall layout of our three step approach to optimizing a stochastic re-

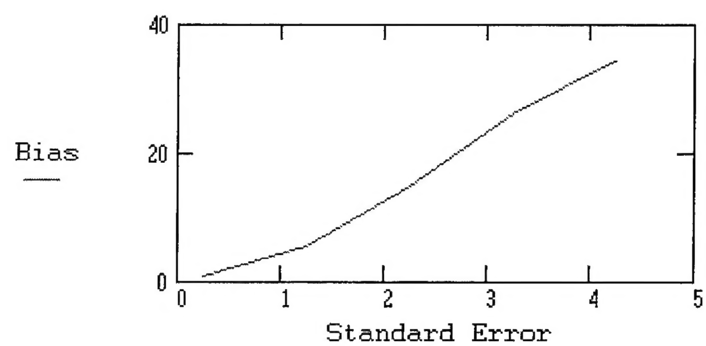



**Figure 3. Bias Inflation.**

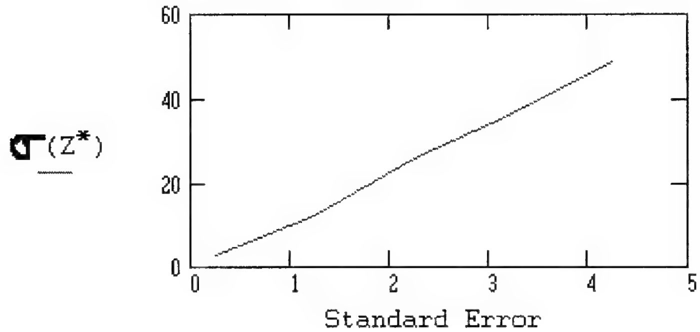



Figure 4. $\sigma(z^*)$ Inflation.

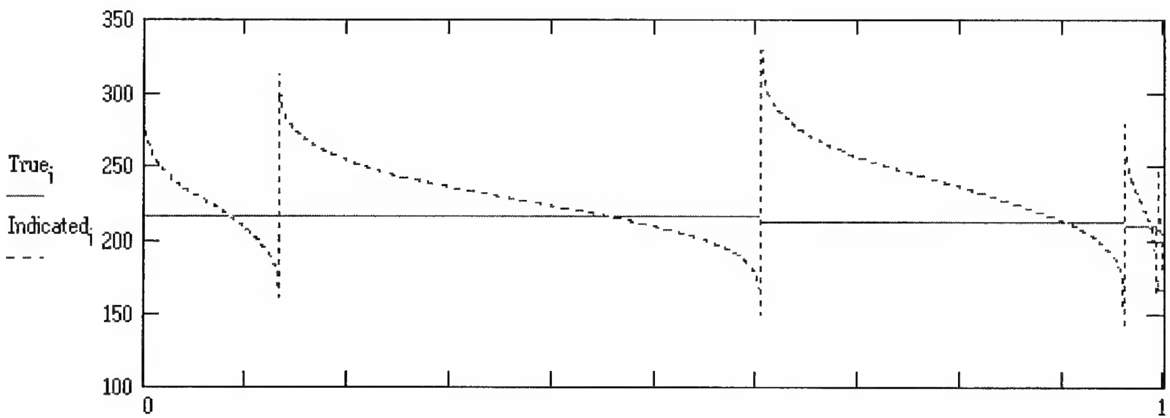



Figure 5. Indicated z* vs. Actual std. error = 2.25.

sponse surface subject to constraints. Step 1 is similar to the traditional approach which estimates $\beta$ in much the same way. In the second and third steps, however, we depart from the traditional approach that takes the estimates $\hat{\beta}$ and proceeds to solve a single linear programming problem whose objective function coefficients are $\hat{\beta}$.

## Step 1: Initial Response Surface

We begin by estimating the response surface coefficients and associated covariance matrix in the customary way. We have seen that using an estimated response surface as an objective function in a linear program can induce bias and inflate the variance of the optimal solution. The next two steps of the process attempt to remedy this problem.

## Step (2a): Sampling Extreme Points

When the variance of the objective function (regression) coefficients is large enough, we may obtain a highly biased solution. This is due to the calculation of an extreme point solution which is not based on the true optimal extreme point. The true optimal extreme point occurs in the case when the objective function coefficients are taken as their true values. Step two shows how to estimate the true extreme point using three methods. The first method samples the generated objective function (in a Monte Carlo fashion) using the variance-covariance matrix from the regression analysis and catalogs the extreme points visited. The second method samples the generated objective function through a design and catalogs the extreme points visited. The third method samples the generated objective function through a parametric sampling approach. This method is sim-

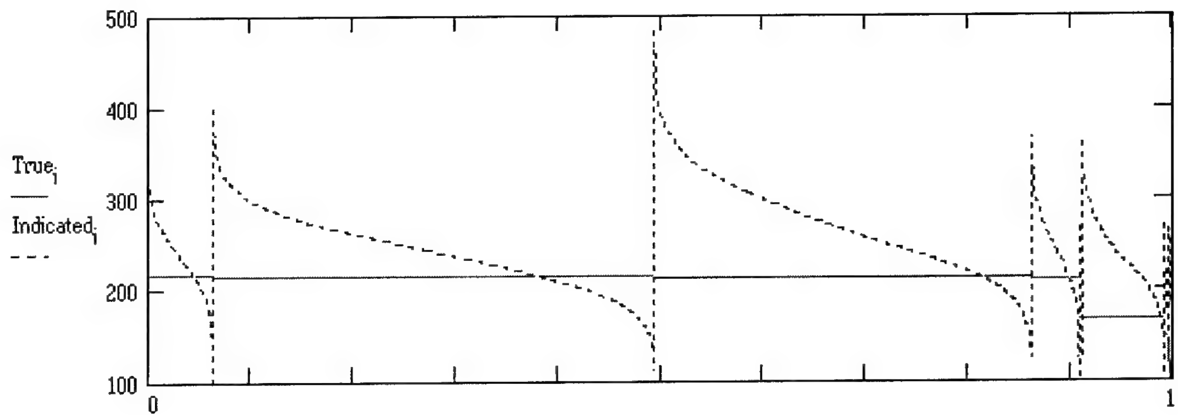



**Figure 6.** Indicated z* vs. Actual std. error = 3.25.

ilar to the design approach, but it relies on information from the parametric analysis from the LP to establish the step size (factor levels) in the experimental design. As we will demonstrate, the parametric sampling approach is vastly superior to the others. We assume that given an initial response surface, its associated variance-covariance matrix, and a large enough sample, we can capture the extreme point corresponding to the optimal solution.

*Monte Carlo Approach* The Monte Carlo sampling procedure consists of sampling from the distribution of the coefficients, i.e., $\hat{\beta} \sim N_p(\beta, \sigma^2(X^TX)^{-1})$, where $\beta$ is estimated by $\hat{\beta}$ and X is the design matrix of decision variables, $\sigma^2$ is estimated by the mean squared error of the regression. We varied $\sigma^2$ as a parameter to *simulate* the effect of various levels of precision in the regression estimates of $\hat{\beta}$. We chose sample sizes to correspond to the sample sizes required in the experimental design alternative so we could compare the success rate for each level of effort. Each sample objective function inserted into the linear programming problem either yields the true optimal extreme point or some other feasible, non-optimal extreme point. The probability that a sample contains the true optimal extreme point improves as the sample size increases. Repetitively generating these samples enables us to estimate the percentage of times the true solution is captured in a sample of a given size. Table I shows the results of the Monte Carlo sampling.

An advantage to Monte Carlo sampling is that, at least theoretically, the size of Monte Carlo samples could be increased indefinitely. While Monte Carlo sampling is the least efficient of the options presented here, it could be an effective brute force approach to sampling the true optimal extreme point. In practice, however, taking a large sample from a large complex system may prove impossible.

*Experimental Design Approach* We chose an experimental design as an alternative to the Monte Carlo approach. We investigated the application of a Box-Behnken design to the space of **c**. Box-Behnken designs are a family of effi-

**Table 1.** Monte Carlo Samples

| Standard Error | .25 | 1.25 | 2.25 | 3.25 | 4.25 |
|---|---|---|---|---|---|
| N = 49 % miss "true" | 1.2 | 4.0 | 5.8 | 12.3 | 18.6 |
| N = 74 % miss "true" | 1.0 | 2.2 | 4.3 | 7.7 | 12.5 |
| N = 100 % miss "true" | .8 | 1.8 | 2.6 | 5.2 | 10.0 |
| N = 200 % miss "true" | 1.0 | 1.8 | 2.6 | 5.2 | 10.0 |
| N = 300 % miss "true" | .8 | 1.3 | 1.5 | 2.3 | 3.7 |
| N = 500 % miss "true" | .5 | .9 | 1.3 | 1.9 | 3.1 |

cient three level designs based on the construction of incomplete block designs. These designs were first presented in Box and Behnken (1960) and are discussed in Box and Draper (1987, p. 519) or Meyers and Montgomery (1995, p. 318). The goal of the designed experiment approach is to identify the true extreme point by systematically investigating the region around our best objective function coefficient estimate, $\hat{c}$.

First we use a modified (only one sample at the center point) Box-Behnken design. This procedure proves somewhat effective. By varying the estimated objective function coefficients by a percentage of their estimated standard deviation (called a standard deviation multiplier) we sample in a method prescribed by the design. The specific multipliers are given in the body of Table 2. Tests using a single Box-Behnken design showed limited success. In our experiments, this design failed to sample the true extreme point as much as 41.6% of the time. In the first two modifications investigated below, we augment the current experimental arrangement with additional design points arrayed according to the Box-Behnken layout with different multipliers.

In a second modification to the standard Box-Behnken design we double the length of the design by sampling at each design point twice. We use different standard deviation multipliers for every identical pair of design points, in effect, transforming a three-level design into a five-level design. Results with the double Box-Behnken design are empirically superior to sampling in a Monte Carlo fashion 49 times (see Table 2). Results over a broad range of problems indicate this design is superior, but not dramatically so, to an equivalent number of Monte Carlo samples. In general, either case fails to give confidence in the results.

The next modification includes adding a third Box-Behnken design to the previous two designs and sampling it using a different standard deviation multiplier–this is a seven-level design. In essence, this is equivalent to sampling from three consecutive designs.

The triple Box-Behnken design demonstrates good results, but requires more samples. In this case, the triple Box-Behnken design (with four decision variables) requires 74 design points. Comparing this result to that of the Monte Carlo experiments with 74 samples reveals that the triple Box-Behnken design captures the extreme point more frequently.

To this point, each design is an improvement over an equivalent number of Monte Carlo samples, but no design gives a high success rate at higher noise levels. In an effort to improve the observed frequency of sampling the true extreme point with higher levels of noise, we investigate another type of modification to the basic Box-Behnken design. In this case, we modify the basic structure at each design point. Instead of sampling at the design points using a three-level approach of 1, -1, or 0, this new design is a five-level design where each design point samples with some combination of 1, -1, .5, .5, or 0. This modification doubles the length of the design and at each design point alternatively samples from either 1 or .5.

The single modified 5-level Box-Behnken design has 49 design points, the same number as the double Box-Behnken design used to produce the results presented in table 2. The 5-level design has a higher success rate in sampling the true optimal extreme point than either the double Box-Behnken design, or an equivalent number of Monte Carlo samples. The 5-level Box-Behnken design represents an improvement

**Table 2.** Box-Behnken Samples

| Standard Error | .25 | 1.25 | 2.25 | 3.25 | 4.25 |
|---|---|---|---|---|---|
| Standard Dev Multiplier (Single) | 2.5 | | | | |
| % Miss "true" | .2 | .8 | 11.5 | 32.7 | 41.6 |
| Standard Dev Multiplier (Double) | 1.5 | 3.0 | | | |
| % Miss "true" | .25 | 0.0 | 1.65 | 9.1 | 20.3 |
| Standard Dev Multiplier (Triple) | .5 | 1.75 | 3.0 | | |
| % Miss "true" | 0.1 | 0.2 | 0.8 | 5.0 | 10.6 |

when sampling at higher noise levels, but significant errors could still exist, see Table 3.

A further modification attempts to decrease the errors in sampling the true optimal extreme point by doubling the design and choosing a different standard deviation multiplier for the second half of the design. This modification is analogous to the change creating the double Box-Behnken design. This design creates a nine-level design. Table 3 contains the results of 1000 replications of this design. This design gives excellent results. This design produced the best results for methods with about 97 samples, and it is competitive with a Monte Carlo method of 200 samples.

In the final modification, another modified 5-level design is added and sampled at a different standard deviation. This 13-level design (four variables) has 145 design points. The results in Table 3 show the excellent results.

The triple 5-level Box-Behnken design was superior to all other designs and even superior to 500 Monte Carlo samples. This design provides excellent sampling in a relatively efficient manner. The main drawback is that it requires 145 samples with only four variables.

*Parametric Sampling Approach* Our next goal was to develop a technique that would give excellent sampling of the true extreme point with a small number of samples. We settled on a methodology that exploits classic parametric analysis and offers a "smarter" step size in each direction of the design, we call this approach Parametric Sampling.

Parametric Sampling is accomplished by determining the break points for basic and nonbasic variables using classic mathematical programming sensitivity analysis. We determine how far we need to step out in a direction before we get a basis change, and this length is the step size used in a design. We used a $\pm 4\sigma$ cut-off on the length of the step size for each variable to avoid unreasonable estimates of the response surface coefficients. Previously introduced designs could now use this "smart" step size. Parametric Sampling proves so effective that a full design is often unwarrented, although the option is available if the need arises. We found a simple design that has a single step on each side of each variable, and a sample at the center point, very effective. This design is called a "one-at-a -time" or "star" design.

Table 4 compares the effectiveness of the various approaches; Parametric Sampling is the clear winner. The numbers in the table represent the percentage of time the true extreme point was missed.

Another interesting consideration is the number of extreme points visited with different sampling techniques. If one sampling method proves highly accurate, but requires more extreme points to be sampled, then it might not be the best design to employ. Fortunately, no design greatly increased the number of extreme points sampled and Parametric Sampling is the most conservative of the approaches. Table 5 illustrates the total unique extreme points sampled for 200 Monte Carlo samples, two 5-Level designs, and Parametric Sampling - results are typical of all sampling options.

## Step 2(b): Screening Extreme Points

In this research, only the objective function is stochastic and therefore only optimality, and not feasibility, is an issue. We want to develop a technique to screen sampled points to see if we can decrease the number of LP solutions

**Table 3.** 5-Level Box-Behnken Type Design

| Standard Error | .25 | 1.25 | 2.25 | 3.25 | 4.25 |
|---|---|---|---|---|---|
| Standard Dev Single | 2.5 | | | | |
| % Miss "true" | .5 | 1.8 | 2.1 | 5.3 | 11.2 |
| Standard Dev Double | 1.5 | 3.0 | | | |
| % Miss "true" | .2 | .3 | 1.0 | 2.6 | 6.8 |
| Standard Dev Triple | 1.5 | 2.75 | 4.0 | | |
| % Miss "true" | 0 | 0 | 0 | .5 | 2.2 |

**Table 4.** Overall Comparison

| Standard Error | .25 | 1.25 | 2.25 | 3.25 | 4.25 |
|---|---|---|---|---|---|
| 48 Samples Double Design | 0.25 | 0 | 1.65 | 9.1 | 20.3 |
| 49 Samples Monte Carlo | 1.2 | 4.0 | 5.8 | 12.3 | 18.6 |
| 73 Samples Triple Design | .1 | .2 | .8 | 5.0 | 10.6 |
| 73 Samples Monte Carlo | 1.0 | 2.2 | 4.3 | 7.7 | 12.5 |
| 97 Samples Double 5-level Design | .2 | .3 | 1.0 | 2.6 | 6.8 |
| 145 Samples Triple 5-level Design | 0 | 0 | 0 | .5 | 2.2 |
| 7 Samples Parametric Sampling | 0 | 0 | 0 | 0 | 2.0 |
| 500 Samples Monte Carlo | .5 | .9 | 1.3 | 1.9 | 3.1 |

**Table 5.** Total Unique Extreme Points

| Standard Error | .25 | 1.25 | 2.25 | 3.25 | 4.25 |
|---|---|---|---|---|---|
| 200 Monte Carlo | | | | | |
| # unique ext. points | 3 | 4 | 6 | 8 | 9 |
| Double 5-level Box-Behnken Type | 1.5 | 2.5 | | | |
| # unique ext. points | 2 | 3 | 5 | 8 | 8 |
| Triple 5-level Box-Behnken Type | 1.5 | 2.75 | 4.0 | | |
| # unique ext. points | 2 | 4 | 5 | 7 | 8 |
| Parametric Sampling | | | | | |
| # unique ext. points | 2 | 2 | 4 | 4 | 5 |

required. Using previously recorded solutions we can evaluate new samples to decide whether the linear program needs to be solved. The optimality condition, for a maximization problem, in the general case is:

$$\hat{\mathbf{c}} - \hat{\mathbf{c}}_B \mathbf{B}^{-1} \mathbf{A} \leq 0 \tag{7}$$

where

$\hat{\mathbf{c}}$ = estimated objective function

$\hat{\mathbf{c}}_B$ = estimated coefficients of the basic variables

$\mathbf{B}^{-1}$ = basis inverse

$\mathbf{A}$ = constraint matrix

As we sample new extreme points their corresponding basis inverses are stored and used to screen new objective function samples. For every new sample of the objective function, we evaluate Equation 7 for each basis inverse stored until we satisfy the optimality condition. If the optimality condition is never satisfied we then solve the linear program to identify a new basis. Using this scheme we solve a linear program only once for each unique extreme point sampled. The improved efficiency will vary from problem to problem, but we found improvement is measured in orders of magnitude. Applying this technique greatly increases the practicality and efficiency of the design sampling techniques. Using this screening procedure makes the triple 5-level Box-Behnken design approach feasible, and increases the applicability of Parametric Sampling to large problems.

## Step 3: Selecting the Optimal Extreme Point

After identifying the feasible extreme points, we no longer need the linear program. We simply use the decision variable settings at any extreme point as input to the simulation to estimate z*. The challenge becomes one of selecting the extreme point that happens to be the true optimal solution. In other words, the objective of Step 3 is to select the "best" alternative. An entire literature of statistical ranking and selection procedures is available to support the objectives of Step 3.

Dudewicz and Dalal (1975) (summarized nicely in Law and Kelton (1991, p. 596)) present ranking and selection procedures for normal random variables that offer an alternative to the brute force method. We used this ranking and selection procedure to analyze the extreme points sampled by the double Box-Behnken type design when the standard error equals 3.25.

After performing a ranking and selection procedure we plot histograms using all simulation samples from the best m alternatives. The histogram can the aid the decision maker by visually representing the possible realizations of the process at given settings. Two important advantages are: avoiding risk by choosing the smallest variance, and illustrating nearly equivalent alternatives and allowing the decision maker to consider factors not captured by the model. A visual representation presents the decision maker with a broader knowledge base from which to make a decision. In this example, the actual variances are equal, but the true strength of this method is evident when the variances differ. Figure 7 illustrates the histograms of the top four alternatives – dotted vertical lines represent the estimated mean for each alternative. The decision-maker now has a way to visualize the trade-offs between the expected value of options and their variance. An alternative to analyzing a histogram of the data is to plot the normal probability curve defined by the estimated mean and variance. At this point the choice is up to the decision maker.

## CONCLUSIONS FROM BASIC RESEARCH

This paper offers an alternative method to the traditional approach of estimating a response surface and then using it as the objective function of a linear program. On average the traditional approach will overestimate the mean response, and it is unlikely we will choose the true optimal extreme point. Variance in the estimates of the response surface coefficients can lead to large variance in the estimation of $z^*$ and a low probability of choosing the correct optimal extreme point $EP^*$.

The results of this research clearly demonstrate that some kind of variance reduction techniques applied to the simulation would greatly benefit the analyst. If the optimal solutions are identified through traditional methods (with only one realization of the process) variance reduction procedures appear to be critical. If the analyst chooses to follow the approach recommended in this research, variance reduction (see Law & Kelton, 1991) will play a key role in minimizing the number of extreme points sampled and aiding in the comparison between competing extreme points.

The basic research presented in this paper resulted in an $80,000 cost avoidance for AF/SA. Later, this research found an application at HQ Air Mobility Command (AMC). To better react to changing budgets in the complex mobility system, the AMC Commander/CINCTRANS requested a method to describe resource relationships and their impact on capability. The desired methodology was to be used to optimize the system given a variety of constraints including cost.

## CAPABILITY BASED ANALYSIS EXTENSION

In an effort to satisfy the tasking from AMC/CC this research evolved into Capability Based Analysis (CBA). The potential of CBA has been articulated by many top leaders in the Air Force and Department of Defense. For example, we demonstrated CBA to: the Secretary of the Air Force, ten four-star Generals (e.g., CINCTRANS/AMC/CC, ACC/CC, CINCSPACE, CINCSTRATCOM, ATC/CC, etc.), commanders of all the Numbered Air Forces, about 180 stars throughout the Department of Defense, civilian military leadership, congressional staff members, federally funded nonprofit research organizations, contractors, and aircraft manufacturing company executives.

CBA uses part or all of the basic approach presented in this paper depending on the nature of the question and the models used, but doesn't stop after identifying the top alternatives. CBA uses the response surfaces and a computer program to graphically portray the interaction between variables and to present convincing sensitivity analyses of the potential "optimal" solutions. It is an interactive computer model allowing the levels of all variables to be set by the user and any variable relationships to be graphically displayed. In addition to a capability analysis, the user can view comparisons of variables in a cost/capability context. CBA goes beyond presenting a series of briefing slides and presents a method for the deci-

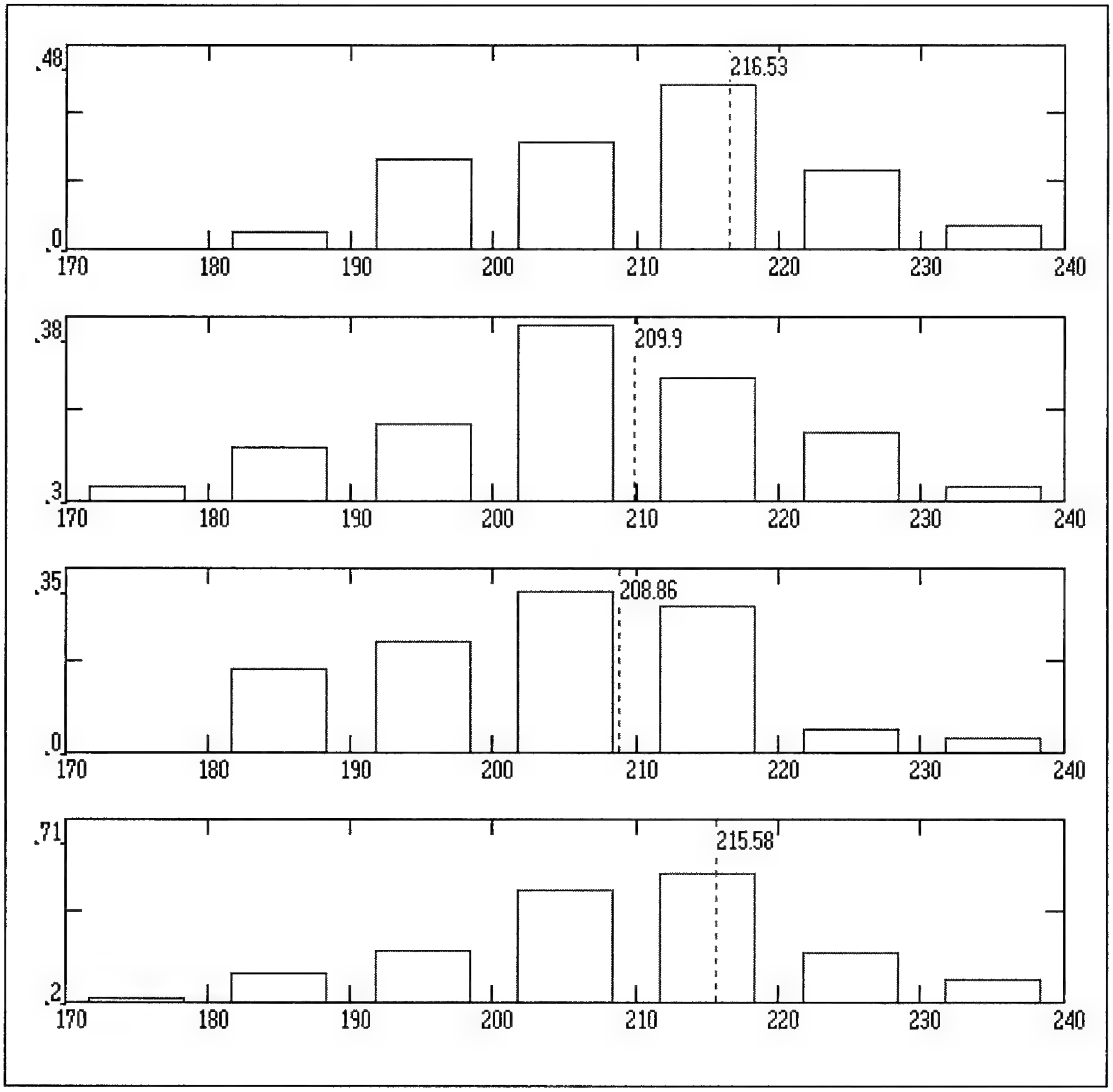



**Figure 7.** Sample Case-Histogram Comparison.

sion maker to interact with the model and explore a variety of options in real-time. For instance, we used CBA to aid in decisions regarding the C-17. The C17 contribution to the overall airlift mission changes as the variables influencing the mission change. Specifically, C-17 analysis results are now given by varying important variables and dynamically presenting the resulting changes in mission effectiveness. Such interactive presentations avoid point solutions and enhance decision-maker awareness of the implications associated with decision alternatives. In practice, CBA has been very effective and very well received. We developed the following with CBA:

1. Models which played a key role in the C-17 Defense Acquisition Board decision on C-17 procurement. CBA was used to present Air Force position to members of Congress and their staffs.

2. A model to assess the effect on capability, in a Southwest Asia scenario, of varying levels

of aircraft, crew ratios (manning), and maximum [aircraft] on the ground (MOG).

3. A force structure analysis evaluating procurement options of military unique aircraft and commercial derivative aircraft, their acquisition and operational support costs and MOG. The subsequent results directly supported C-17 and commercial derivative decisions, enhancing the image of the C-17 and pointing to a specific wide-body commercial cargo aircraft as a possible addition to the airlift fleet.

4. A detailed European infrastructure model illustrating the relationship among the MOG at seven bases at varying levels of operation.

5. A Somalia based airlift model illustrating varying levels of aircraft and concept of operations effect on throughput.

6. A model of the C-17 capability in the third world. Exploring the effects of unique C-1 7 capabilities under austere conditions.

7. A model of C-141/C-5 aircraft maintenance manning requirements. Pointing towards major reductions in the maintenance manning levels.

8. A model which determined the number of C-5s required for training, and allowed two C-5s to be freed for use in Somalia Airlift (Altus AFB).

CBA is an interactive model and as such it is impossible to convey its impact on the printed page. Figure 8 is an example of the initial computer screen for the force structure model; it incorporates six aircraft levels, MOG, the Civil Reserve Air Fleet (CRAF) level, years of program, aircraft procurement cost, operations and support cost, different buy profiles of the C-17 (effecting cost and total force capability over time), and C17 sunk costs.

All graphs produced using CBA are dependent on the levels of other variables in the model. Some interesting insights can be found in the following graphics. Figure 9 shows two graphics illustrating a head-to-head comparison of. C-5s vs. C-17s, and C-141s vs. KC-10s in a high MOG (ample ground support and parking for aircraft) scenario. The figure to the left indicates a linear relationship between C-5s and C-17s, where the aircraft are roughly equivalent and contribute about the same tons per day to the scenario. The figure to the right indicates a linear relationship between C-141s and KC-10s, where the KC-10 contributes more tons per day per aircraft to the scenario.

| Cost | Years | Sunk | C17 buy | C5 | C141 | C17 | B767 | B747 | KC10 | MOG |
|---|---|---|---|---|---|---|---|---|---|---|
| No | 30 | No | ProgBuy | 70 | 64 | 0 | 0 | 0 | 26 | 40 |
| | CRAF: II | | Cost : | 539 | 252 | 564 | 200 | 300 | | |

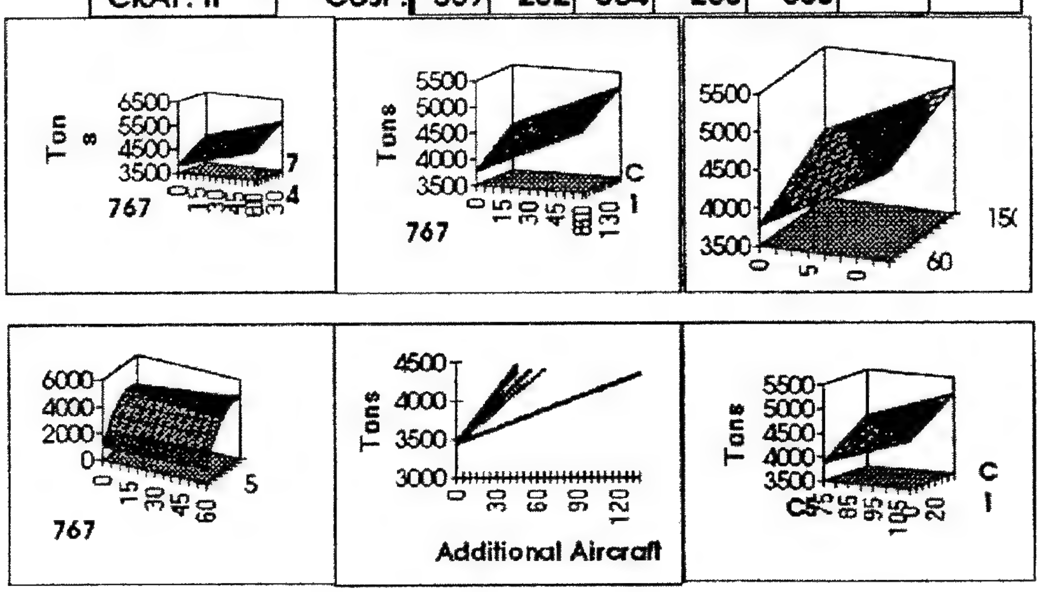



Figure 8. Initial CBA Computer Display.

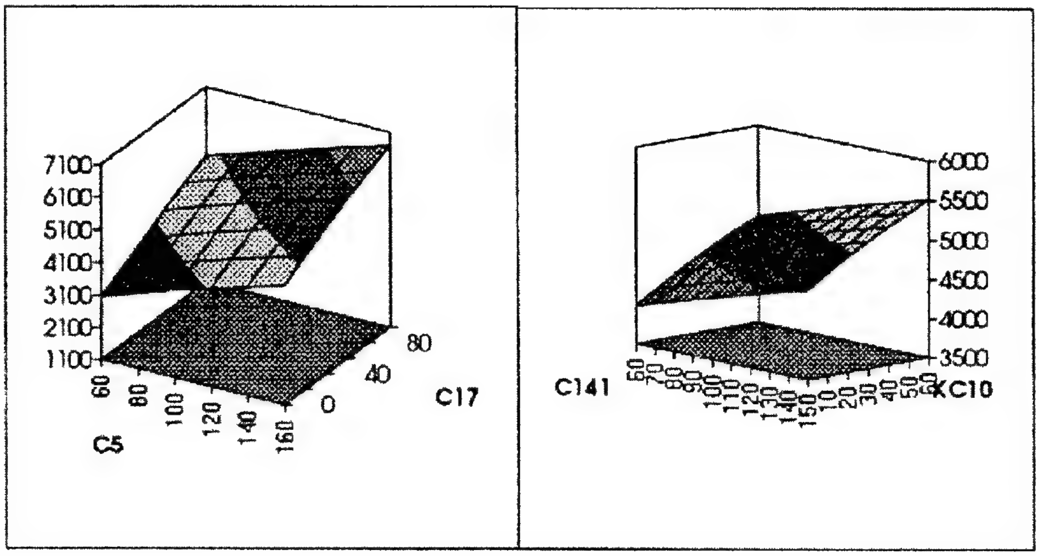



**Figure 9.** High MOG C-5 vs. C-17, and C-141 vs. KC-10.

Figure 10 is a contrast with Figure 9, and the same head-to-head comparison, but in a low MOG scenario (analogous to Split in Bosnia, or Mogadishu in Somalia). The figure to the left indicates an approximate linear relationship between C-5s and C-17s, where additional C-5s contribute to a slight increase in tons per day, but additional C-17s contribute a dramatic increase in tons per day relative to the C-5. The figure to the right indicates a dramatic nonlinear relationship between C-141s and KC-10s, where both aircraft offer increases in throughput, as the number of aircraft increases, to a point. If additional aircraft are forced into the aircraft flow beyond that point, then throughput would actually decrease. This comparison illustrates a case where a local optimum can be found.

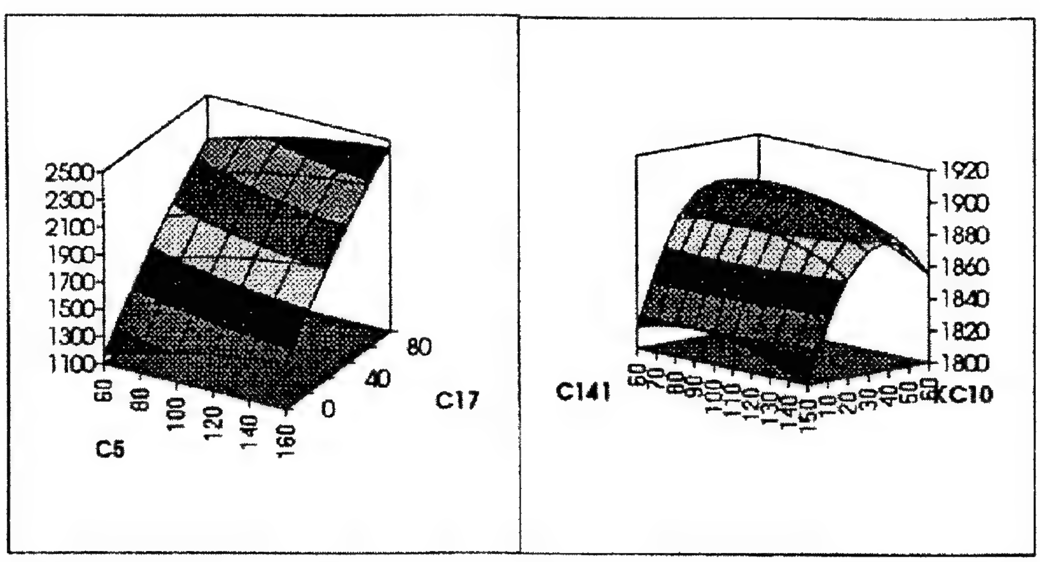



**Figure 10.** Low MOG C-5 vs. C-17, and C-141 vs. KC-10.

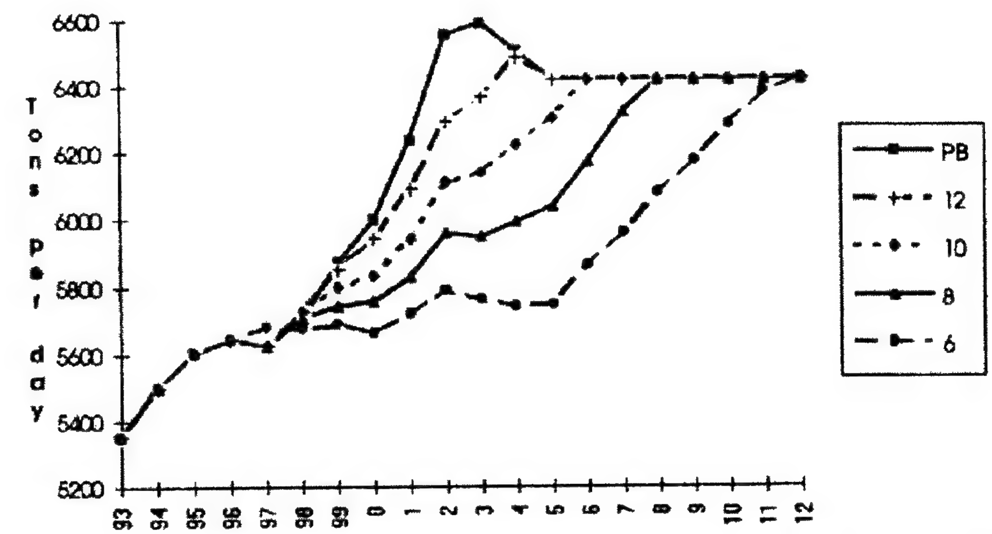
Figures 9 and 10 only illustrate a comparison between aircraft with respect to throughput in tons per day, but comparisons can be made between any quantifiable resources and compared with respect to capability and cost.

Figure 11 adds time as a component and illustrates an interactive planning tool that shows how the capability of the total fleet varies over time, different MOG levels, and varied aircraft procurement/retirement schedules. The lines on the graph represent different C-17 procurement schedules. The input sheet below the graph allows all the input data to be changed, and instantly reflected above. Other graphics exist that allow comparisons of more aircraft.

CBA has the ability to quickly characterize the interaction of resources in complex systems, and allows the user to perform timely sensitivity analyses over a broad range of parameter values. Mathematical programming is also used to direct the user to potentially good mixes of resources and the allows the investigation of that region and a way to present the conclusions to a decision maker.

## CONCLUSIONS FROM CBA

The initial application of CBA to the AMC force structure problem has led to direct requests to employ this methodology to other complex problems facing AMC. As such, CBA offers a possible way to help solve a major problem in the analysis community-how to




| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| C5 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 | 109 |
| C141 | 214 | 214 | 217 | 211 | 194 | 176 | 158 | 136 | 128 | 128 | 100 | 82 | 64 | 64 | 64 | 64 |
| KC10 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 | 26 |
| C-17 Buy Profile | | | | | | | | | | | | | | | | |
| PB | 3 | 11 | 16 | 20 | 24 | 34 | 48 | 61 | 76 | 93 | 102 | 102 | 102 | 102 | 102 | 102 |
| 12 yr | 3 | 11 | 16 | 20 | 24 | 35 | 47 | 58 | 68 | 79 | 90 | 101 | 102 | 102 | 102 | 102 |
| 10 yr | 3 | 11 | 16 | 20 | 24 | 35 | 44 | 52 | 60 | 69 | 78 | 87 | 96 | 102 | 102 | 102 |
| 8 yr | 3 | 11 | 16 | 20 | 24 | 34 | 41 | 48 | 54 | 61 | 68 | 75 | 82 | 89 | 97 | 102 |
| 6 yr | 3 | 11 | 16 | 20 | 27 | 32 | 38 | 43 | 48 | 52 | 58 | 62 | 67 | 73 | 78 | 84 |
| Year | 93 | 94 | 95 | 96 | 97 | 98 | 99 | 00 | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 |

**Figure 11. Total Force Capability over Time.**

present a complicated analysis to a decision maker in a clear and concise manner that motivates action.

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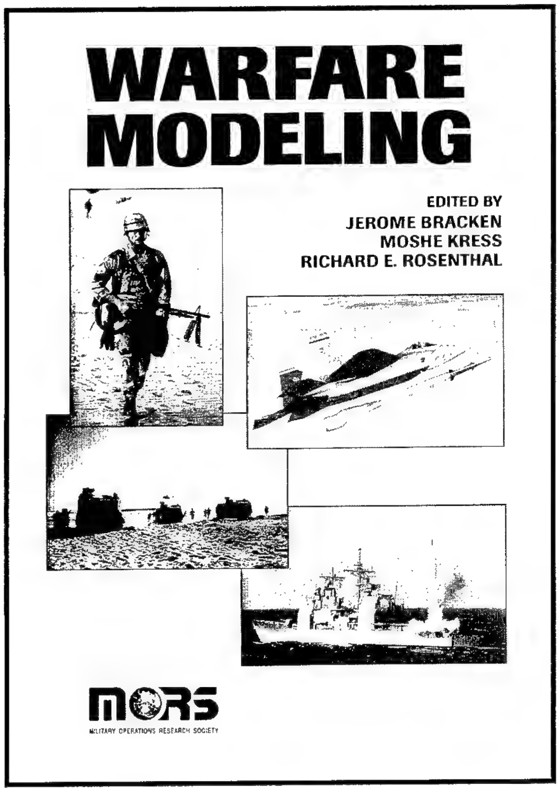


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# Ardennes Campaign Simulation (ARCAS)

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*APPLICATION AREA:*
Land Warfare

*OR METHODOLOGY:*
Wargaming, Combat Simulation Verification and Validation

## ABSTRACT

The Ardennes Campaign Simulation (ARCAS) study was performed to improve the credibility of the Stochastic Concepts Evaluation Model (STOCEM), a theater-level combat simulation, by comparing the outcome of a STOCEM simulation of the World War II (WW II) Ardennes campaign of 1944–45 (also known as the Battle of the Bulge) with historical campaign results.

Historical campaign data had been developed, using archival sources, into a computerized data base denoted as the Ardennes Campaign Simulation Data Base (ACSDB). The initial positions, configuration, strengths, compositions and availability of forces for the campaign, as depicted in the ACSDB, are used to define the STOCEM force laydown. Representative simulation results (front line movement, major system losses, and personnel casualties) are compared with historical results from the ACSDB. Stochastic variability of model results is also quantified in terms of confidence limits about each sample mean and bounds on sample outcomes. The comparison of simulation results with history is used to develop guidelines for investigating algorithmic changes which may improve model credibility of the STOCEM. Insights on model verification and validation (V & V) are also developed.

Study results indicate that ARCAS STOCEM tends to generate more force movement, weapon system losses, and personnel casualties than occurred in history. Investigations of potential changes to STOCEM logic/inputs suggested by the simulation/history comparisons include simulation of a "breakthrough" attack posture, moderation of attacker move rate in response to a sustained rapid combat advance, and reduction of base lethality against armor for an attacker possessing a high strength advantage.

## 1. INTRODUCTION

Army Regulation (AR) 5-11 prescribes policy on the verification, validation, and accreditation of Army models. Validation of a theater level combat simulation requires the translation of a real-world military campaign into a data structure which is comprehensive and compatible with inputs and outputs for the simulation model. Using a complete and consistent historical data base for a campaign to develop input initial battle conditions for a combat simulation enables generation of a model representation of that campaign. Subsequent comparison of simulation and historical outcomes is then useful for application of the validation policy of AR 5-11 and for assessment of potential modifications in combat model algorithms which may enable the model to better reflect real combat (as reflected in history).

The Director of the US Army Concepts Analysis Agency (CAA) initiated construction of a new historical database describing the 1944–45 Ardennes Campaign of World War II. He also proposed that the database should be configured so that initial battle status and conditions could be translated into inputs for the Concepts Evaluation Model VII (CEM VII), a fully automated combat simulation. Simulation results could then be compared with historical outcome data. These comparisons could be used to suggest areas of investigation for potential changes in rules, algorithms, and capabilities of the CEM VII, which might improve model capability and credibility.

In September 1987, the Historical Evaluation and Research Organization, a division of Data Memory Systems, Incorporated, was issued a contract to construct, based on archival sources, a comprehensive computerized historical data base of the WW II Ardennes campaign. This DBASE IV data base, designated as the Ardennes Campaign Simulation Data Base (ACSDB), was completed in December, 1989. The ACSDB was created using primary and secondary sources on file at libraries and archives in the United States, Great Britain, and the Federal Republic of Germany.

The combat simulation chosen for representing the campaign in the comparison with history was the Stochastic CEM (STOCEM), a stochastic version of the CEM VII. The corresponding ARCAS study was completed in 1995. ARCAS study results are summarized in this paper and are documented in a CAA study report (Bauman, 1995).

## 2. PROBLEM AND OBJECTIVES

The problem is to compare a computerized combat model representation of the WW II 1944–45 Ardennes Campaign with a data base of historical results from that campaign in order to assess and improve combat model credibility and capability.

The historical data base, the ACSDB, is used to define initial conditions for the Ardennes Campaign simulation.

The objectives are to subsequently compare combat simulation outcomes with historical data to assess:

- the appropriateness and verisimilitude of simulation algorithms.
- areas of investigation for potential changes or improvements in rules, algorithms, and capabilities of the combat model employed.
- support for verification and validation (V & V) of the combat simulation.

Within the US Department of the Army, validation of a simulation model is defined in AR 5-11, as the process of determining that the model is an accurate representation of the real-world entity from the perspective of the intended use of the model. In the strictest sense, a combat model must be validated by selecting many actual conflicts of forces as baselines and then attempting to represent and reproduce the attributes, components, and events of those baseline conflicts in the simulation. Because the real world is subject to uncertainty, stochastic variation is appropriate in simulated combat processes, events, and outcomes.

In ARCAS, stochastic simulation results are generated and compared with historical outcome data from the ACSDB, which is a single point sample from the unknown distribution of real world outcomes realizable from the initial campaign conditions. The statistical suitability of using the ACSDB as a surrogate for the unknown distribution can not be quantified. The immediate usefulness of alternative modelling rationales suggested in this paper is therefore constrained to investigative value only. The use of theater measures in ARCAS comparisons does tend to maximize the usefulness of the ACSDB as an historical baseline, since aggregated theater statistics, especially in a large conflict, usually have considerably less variability over samples than do measures from component battles at division or corps level.

The intent of ARCAS is not to adjust model inputs to force simulation results to mimic history. Instead, the aim is to simulate the Ardennes campaign in the STOCEM by setting initial conditions using the force structure and laydown of the historical campaign, while allowing the dynamic combat rules/algorithms of the simulation free rein to generate the flow and tempo of simulated combat. Simulated and historical combat outcomes are then compared to determine where and why patterns of simulated combat are similar to, or differ from, patterns reflected in the associated historical campaign. As rationales for differences between simulation results and history are discerned, logically justified, and quantified, they suggest areas of investigation into alternative simulation process algorithms which can improve model realism and credibility.

The ARCAS study effort represents only the first phase of a larger work in progress. The assessments and suggestions developed in this paper are essentially hypotheses which must be verified, or modified, through additional testing and analysis using more, and different, historical samples.

## 3. METHODOLOGY

The basic approach, portrayed in Figure 1, consists of construction of a historical database for the Ardennes campaign, use of the database to develop input data for the campaign representation in the combat simulation, execution of the combat simulation, comparison of simulation results with history as recorded in the historical data base, assessment of similarities and differences in these comparisons, and consequent suggested areas of investigation which might result in improvements to the simulation.

The historical data base provides initial positions, configuration, strengths, compositions and availabilities of forces for the campaign, which are used to define the force laydown for ARCAS STOCEM. Effectiveness parameters (e.g. range, rate of fire, lethal area/probability of kill given a hit) of weapon systems employed in the Ardennes campaign are generated for input into a STOCEM preprocessor. Intrinsic munitions effectiveness measures not available in WW II historic data are determined by interpolation and extrapolation of test results from comparable weapons.

The combat simulation used in ARCAS is the Stochastic Concepts Evaluation Model (STOCEM) developed, documented (Johnson 1992), and used by CAA. The STOCEM is a stochastic version of the Concepts Evaluation Model VII (CEM VII), which is an operational combat simulation used, at CAA, to assess capabilities and requirements of forces in theater-level scenarios.

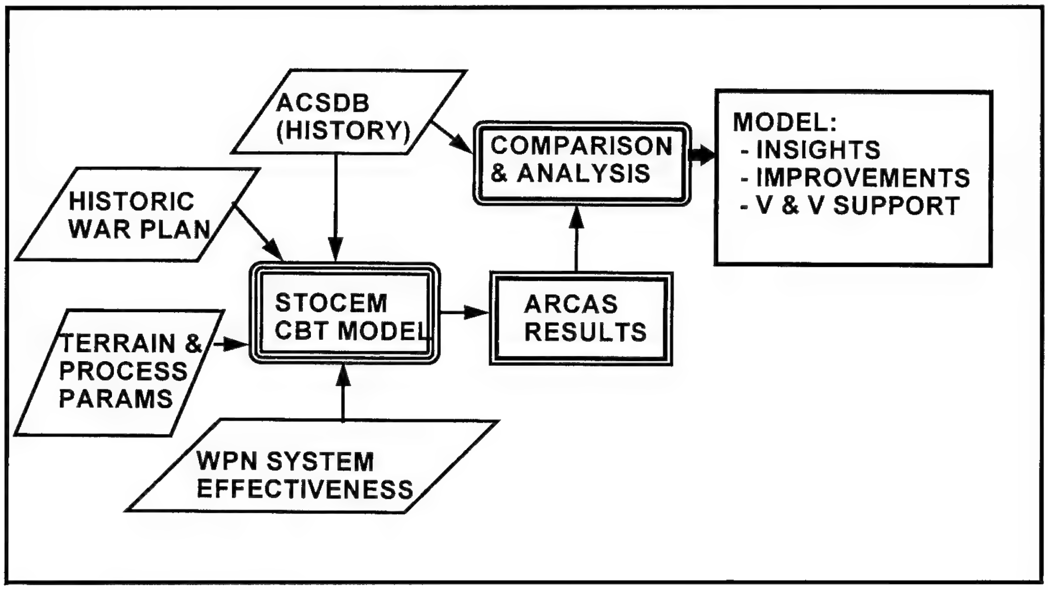


**Figure 1. ARCAS Methodology Approach.**

The ARCAS STOCEM scenario is executed for exactly 16 simulation replications. Comparisons (ARCAS STOCEM vs. history) are usually made and portrayed at 4-day intervals during the campaign scenario. Campaign outcome measures used for comparison include personnel casualties, weapon system kills, ammunition consumption, and progress/position of the forward edge of the battle area (FEBA). Casualties are assessed only for committed line units and artillery units, and are expressed in terms of personnel killed in action (KIA), wounded in action (WIA), captured and missing in action (CMIA), and disease/nonbattle injury (DNBI).

A weapon system is defined as lost, or "killed", if it is destroyed or abandoned. Generic weapon system classes used in comparisons herein include tanks, armored personnel carriers (APCs), artillery, and a class, denoted by AT/M, comprising anti-tank systems and mortars. For each side (force), STOCEM explicitly represents up to 12 different categories in each of the above weapon classes. These categories are combined into a single generic class (e.g., tanks) for the results presented in this paper.

The FEBA progress is expressed as the average magnitude, in kilometers (km), of forward or retrograde movement made by the German battle front since the start of the campaign.

## 4. STOCEM

STOCEM is a two-sided fully automated stochastic theater combat simulation. Units in STOCEM are resolved in terms of BLUE brigades and RED divisions. Unit combat is simulated in 12-hour (simulated time) cycles. Decision logic is executed at 12-, 24-, 48-, and 96-hour simulated time intervals associated with simulated command levels corresponding to unit (brigade or division), corps, army, and theater. STOCEM simulates direct fire engagements only between line units, but higher echelons allocate fire support over their area of control. Attrition from close air support is also simulated.

During the 12-hour simulated unit combat cycle, after the rounds available to shooters have been determined, an attrition processor called ATCAL (Attrition Model Using Calibrated Parameters) is used in STOCEM to determine combat losses during the period. ATCAL uses killer-victim scoreboards and ammunition expenditure tables generated by a preprocessor, the Combat Sample Generator (COSAGE).

The COSAGE killer-victim scoreboards reflect kills per round fired for a large spectrum of shooter types, target types, and engagement/posture combinations over a wide range of small engagements simulated by COSAGE.

During STOCEM execution in a simulated combat cycle, the ATCAL processor extrapolates and interpolates the appropriate killer-victim scoreboards (generated by COSAGE for the forces and engagement type involved) to yield the resulting attrition of systems and personnel.

STOCEM introduces probabilistic variation into combat processes and decisions to yield a stochastic distribution of possible battle outcomes. Stochastically modeled combat processes in STOCEM include decision processes regulating mission selection and commitment of forces, weapon attrition generated from ATCAL results, fraction of damaged weapon systems that are killed or abandoned, the casualty type partitioning of personnel casualties, and the attacker rate of advance. The rate of advance is a function of tactical situation parameters such as terrain, posture, and the relative combat losses of the opposing combatant units.

The STOCEM theater (battlefield area) for ARCAS, as shown in Figure 2, is overlaid with 21 indexed avenues of advance which are used by the forces simulated in the scenario. These avenues, labeled #10 through #30, are represented as dashed lines in the figure. These serially (north-south) indexed avenues provide a convenient way of representing FEBA progress on a Cartesian coordinate system (as km progress on each avenue of advance).

## 5. SCENARIO

The scenario timeframe is the period between December 16, 1944 (denoted as D-Day) and Jan 17, 1945 (denoted as D+32). Each unit's availability for commitment during the scenario is based upon the day when initial combat engagement is first recorded for that unit in the historical data. The US/UK forces operate primarily in defensive and static postures during the first part of the campaign, and shift to counteroffensive roles in the last half of the campaign.

The German Armies represented in the initial attack include, from north-to-south, the 6th Panzer Army, the 5th Panzer Army, and the 7th Panzer Army. Twelve German combat units (mostly divisions) are on-line and engaged at D-Day. A further 16 line units reinforce these during the campaign. Fire support for echelons

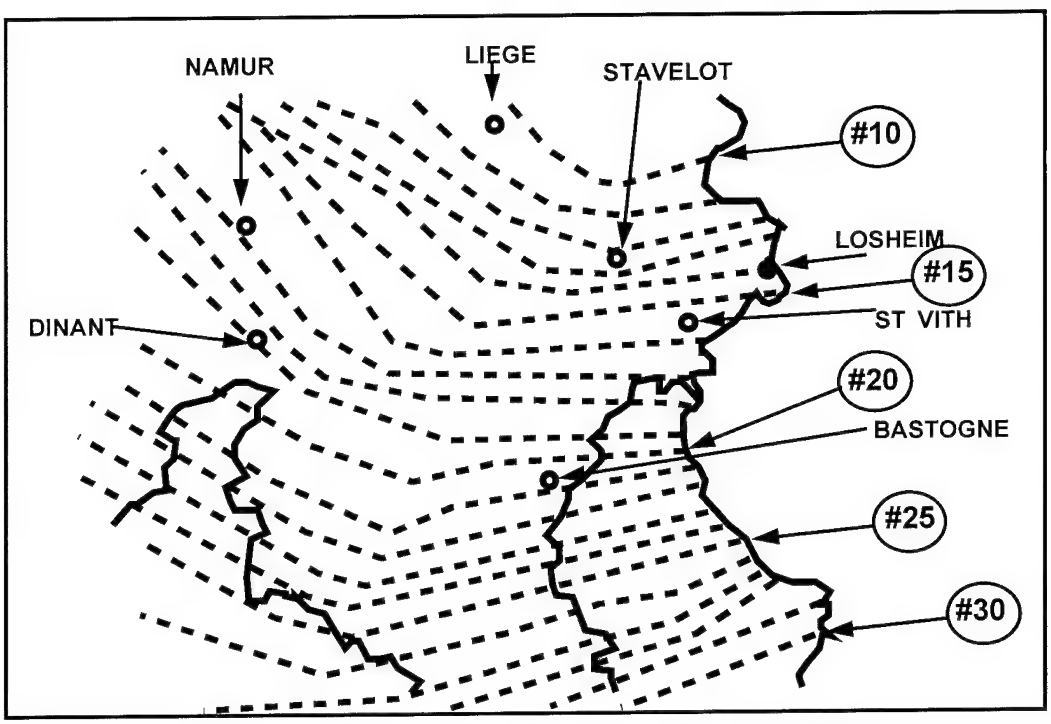


**Figure 2. STOCEM ARCAS Theater with Avenues of Advance**

above division comes from three armies and 14 corps.

The initial US/UK forces opposing the German attack on D-Day are, as positioned from north-to-south, elements of US V Corps, US VIII Corps, and US III Corps. Six US divisions are on-line and engaged at D-Day. A further 24 line units (21 US and 3 UK) reinforce these during the campaign. Fire support from echelons above division are from two US armies, six US corps, and one British corps.

The ARCAS STOCEM scenario partitions each theater force into three areas of operations, corresponding approximately to the sectors of operation for the major Army areas. ARCAS STOCEM then directs each reinforcing unit (for both sides) to the area of operations which it historically supported.

## 6. REPRESENTATION OF STOCHASTIC UNCERTAINTY

The following statistical measures characterize each ARCAS STOCEM outcome measurement used to quantitatively portray the range and likelihood of simulated combat outcomes:

- **Mean.** The ARCAS mean is an arithmetic average over all 16 replications.
- **Maximum value over all replications.** For FEBA progress, the maximum corresponds to the westernmost position of the FEBA, on each avenue of advance, over all replications.
- **Minimum value over all replications.** For FEBA progress, the minimum corresponds to the easternmost position of the FEBA, on each avenue of advance, over all replications.
- **Confidence limits for the STOCEM mean.** The computed STOCEM mean is only a sample estimate of the "true mean", which corresponds to an average computed from an infinitely large sample. Confidence limits, which have at least a specified probability of containing (i.e. bounding) the "true mean", are:
  - — an upper confidence limit defined as [sample mean + 3.16 standard errors]
  - — a lower confidence limit defined as [sample mean − 3.16 standard errors].

where the standard error for the ARCAS samples is defined as [standard deviation/$\sqrt{16}$].

Application of Chebyshev's theorem (Hogg and Craig 1965) provides near-assurance that the limits defined above are, at least, 90% confidence limits regardless of the unknown probability distribution of average outcomes (for a STOCEM measure). If that probability distribution is normal, then the above-defined bounds are at least 99% confidence limits. Charted results have these limits labeled as +3.2SE and −3.2SE respectively, because they are (approximately) 3.2 standard errors distant from the mean.

## 7. ANALYSIS OF FEBA PROGRESS RESULTS

We first compare the simulated and historical movement of the FEBA during the course of the Ardennes campaign. Both the geographic position of the FEBA and its movement over time are compared. Observations impacting on simulation validation, and areas of investigation for potential CEM logic modifications which may improve model realism, are then developed from the ARCAS STOCEM/history comparisons.

## 7.1. FEBA COMPARISON (SIMULATION VS HISTORY)

Figure 3 depicts a map showing a comparison of the simulated ARCAS FEBA on D + 8 with the ACSDB-based historical FEBA on that date.

The following FEBA representations are shown on the figure:

- The CEM maximum FEBA is a line connecting the westernmost simulated FEBA positions, over all replications, on each ARCAS STOCEM avenue of advance.
- The CEM minimum FEBA is a line connecting the easternmost simulated FEBA positions, over all replications, on each ARCAS STOCEM avenue of advance.
- The CEM average (mean) FEBA is a line connecting the average simulated FEBA positions, over all replications, on each ARCAS STOCEM avenue of advance.
- The History FEBA on D+8 is determined from unit location records in the ACSDB.

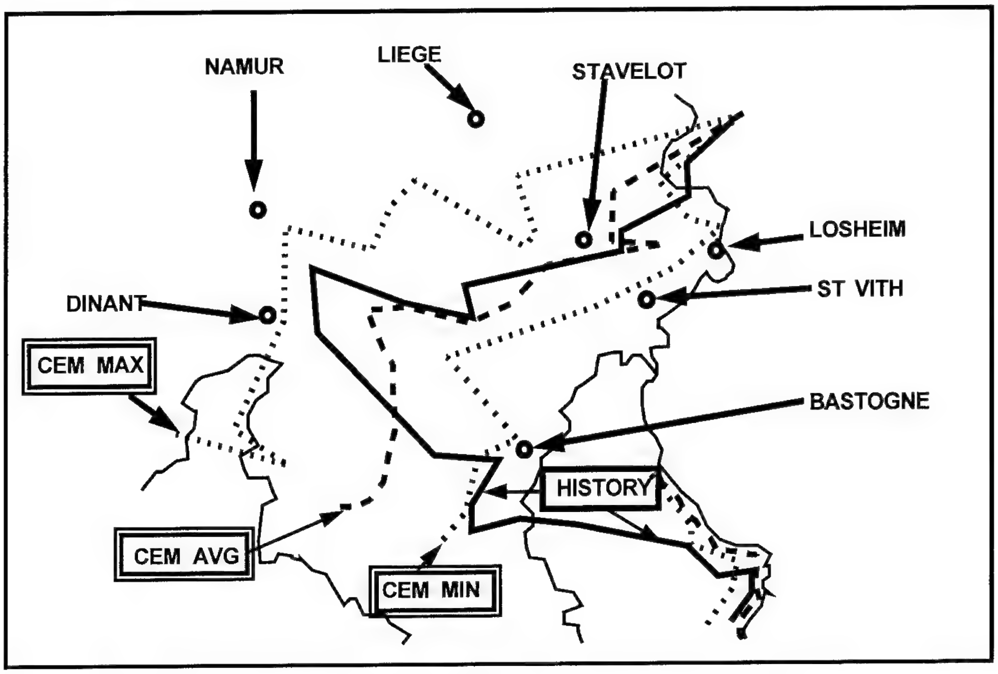


**Figure 3. ARCAS STOCEM FEBA vs. History on D+8.**

The ACSDB does not explicitly define a historical FEBA. Each ACSDB unit, on each day, consists of multiple reported geographic "unit points", each with a separate location. For a specified positive number, P, define the FEBA position for a force along an avenue of advance as the average location of the forwardmost P % of all ACSDB unit points in that force which are in that avenue, and are associated with committed units of that force on that day. Treating each such computed FEBA position as a point location at the midpoint of the associated avenue of advance, define the force FEBA as the set of FEBA positions for that force over all avenues of advance. When German and US/UK FEBAs based on this method are computed, the average of the (German vs. US/UK) FEBA position differences along the avenues of advance is smallest when P is approximately 40%. Since the Germans were the initial attacker, the German FEBA based on that P value is chosen as the historical FEBA for this analysis. Therefore, the "History FEBA", on a given day, is defined in this paper as the average location of the westernmost 40% of that day's ACSDB points associated with the committed German units on (i.e. closest to) each ARCAS STOCEM avenue of advance. This History FEBA is then compared with the ARCAS STOCEM FEBA, which is a well-defined simulated set of forward positions.

In this geographic representation, the ARCAS STOCEM average FEBA shows a clear configurational similarity to the historical "bulge" on D + 8, which is the approximate German "high water mark" of the historical campaign. Especially noteworthy is the similarity in the position of the "spike" pointing toward Namur in both the STOCEM and historical FEBAs.

Figure 4 portrays the relative positions of each FEBA shown in Figure 3, along with uncertainty measures, in a stylized Cartesian coordinate system representation. The figure has linear Cartesian plots showing FEBA progress, measured along each of the 21 ARCAS STOCEM avenues of advance, along with measures of simulation uncertainty.

The vertical axis of the figure shows the FEBA movement (in km), relative to D-day positions, along each CEM avenue of advance. Negative values denote forward (westward) German movement. Positive values indicate retrograde (eastward) German movement. The

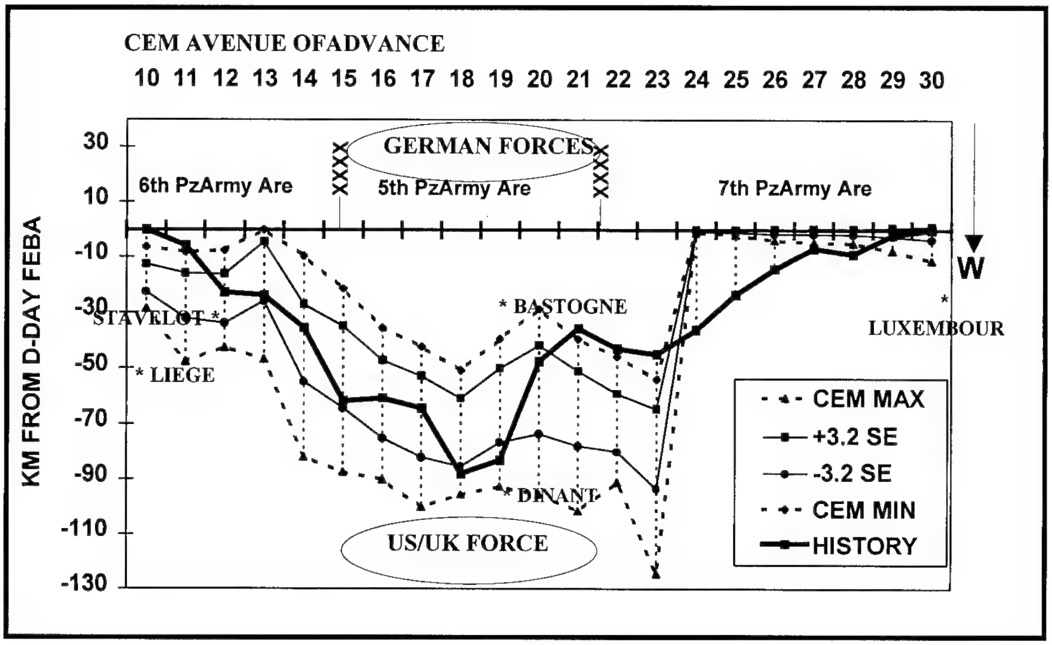


**Figure 4. ARCAS STOCEM FEBA vs. History on D + 8 (with uncertainty).**

avenues of advance are depicted in a north-to-south ordering, which is visually read from left-to-right, along the horizontal axis. Only one point is plotted in the figure for each measure on each avenue of advance. The lines connecting these points are added only to facilitate a visual comparison.

This stylized representation emulates a quasi-geography of the theater with the avenues of advance represented as parallel straight lines. The portrayed orientation is analogous to an aerial perspective facing eastward from above US/UK lines. Army boundaries for the three German Panzer Armies are also shown.

Plotted points in the figure show the measures of statistical variability in ARCAS STOCEM outcomes. The average STOCEM FEBA progress along each ARCAS STOCEM avenue of advance (not shown) is midway between the depicted confidence limits (labeled +3.2SE and −3.2SE).

In this stylized D + 8 FEBA representation, although the History FEBA is not always within the STOCEM 90% confidence limit band, that band is configurationally very similar to the historical "bulge" in the 5th Panzer Army Area (avenues of advance 14 through 21.)

The most noteworthy deviation between ARCAS STOCEM and history is the nearly complete lack of any STOCEM FEBA progress in the seven southernmost (rightmost on Figure 4) avenues of advance. This contrasts with an average historical advance of 13 km on those avenues, varying from 36 km at the southern boundary of the "bulge" to 0 km near Luxembourg.

Figure 5 graphically portrays the progress of the average ARCAS STOCEM FEBA at 4-day intervals and contrasts it with the average History FEBA.

The line graphs in the figure show average FEBA progress (STOCEM and historical) over the entire theater. The bar graphs in the figure show FEBA progress averaged only over the 5th Panzer Army area, which comprised most of the historical "bulge".

The average FEBA progress for the theater on a day is defined as the simple arithmetic average of the FEBA progress on each CEM avenue of advance in the theater on that day. The average FEBA progress for the 5th Panzer Army area on a day is defined analogously except that the average is only over the avenues

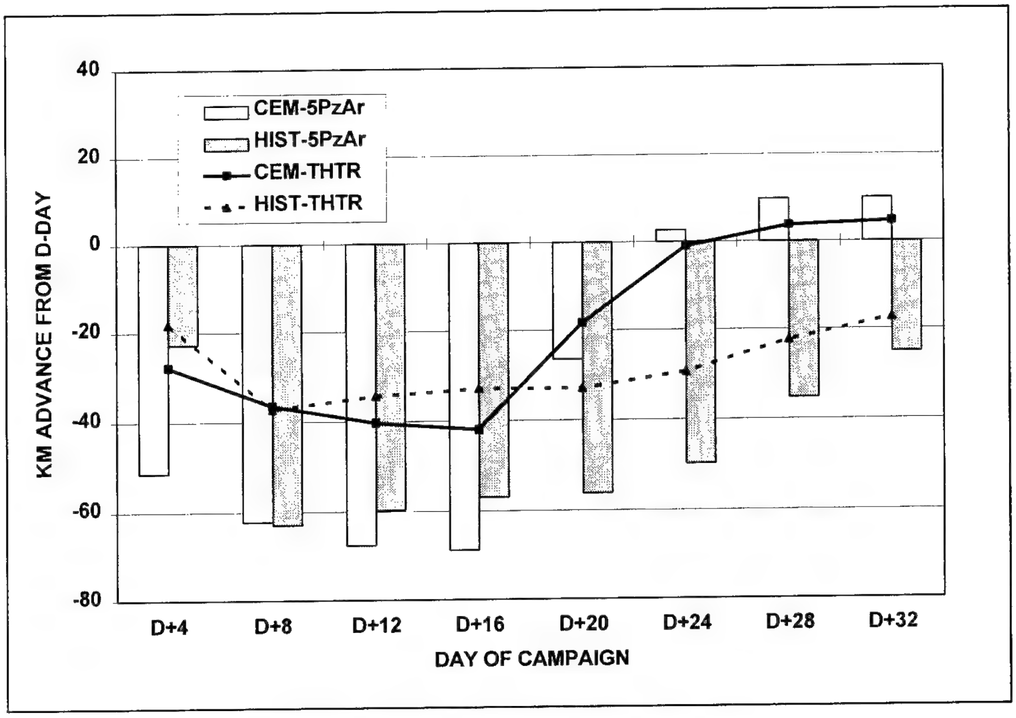


**Figure 5. Average FEBA Progress over Time**

of advance in the 5th Panzer Army area (avenues 14 through 21).

From the depicted average FEBA progress over time, it is apparent that the initial German advance in ARCAS STOCEM is considerably more rapid than occurred historically in the "bulge", but is only moderately greater when averaged over the entire theater. After D + 4, average ARCAS FEBA progress is very similar to history through D + 16 over both the "bulge" and the entire theater. The similarities here support the credibility of the ARCAS STOCEM simulation process.

After D + 16, Figure 5 shows the counterattacking US/UK force in ARCAS STOCEM inducing a German retreat at a considerably more rapid rate than occurred historically.

The STOCEM FEBA progress is related to the engagement postures of committed units. Commitment availability of units was scripted to parallel the historical availability. The change in US/UK force mission from defensive and static to a counteroffensive role was regulated by simulation inputs which enabled a counteroffensive only when the number of committed US/UK reinforcing units reflected sufficient relative strength to doctrinally permit it. Figure 6 shows the percent of the committed US/UK force in simulated attack posture during each 4-day period in the ARCAS STOCEM scenario. The most rapid US/UK advance in ARCAS STOCEM occurs during the eight days ending at D + 24, when it has the largest fraction of its committed force in the attack posture.

## 7.2 ASSESSMENT OF FEBA COMPARISONS

*a. Causes of Differences.* One possible cause of the excessively rapid ARCAS FEBA movement during the US/UK counterattack may be that the placement and concentrations of forces generated by a fully automated model, such as STOCEM, may induce a stronger rollback of a weaker opponent than will be achieved by a less efficient and more cautious actual attacking force. An actual combat force deploys its units less effectively than the STOCEM algorithms, and, affected by human factors and perceptions

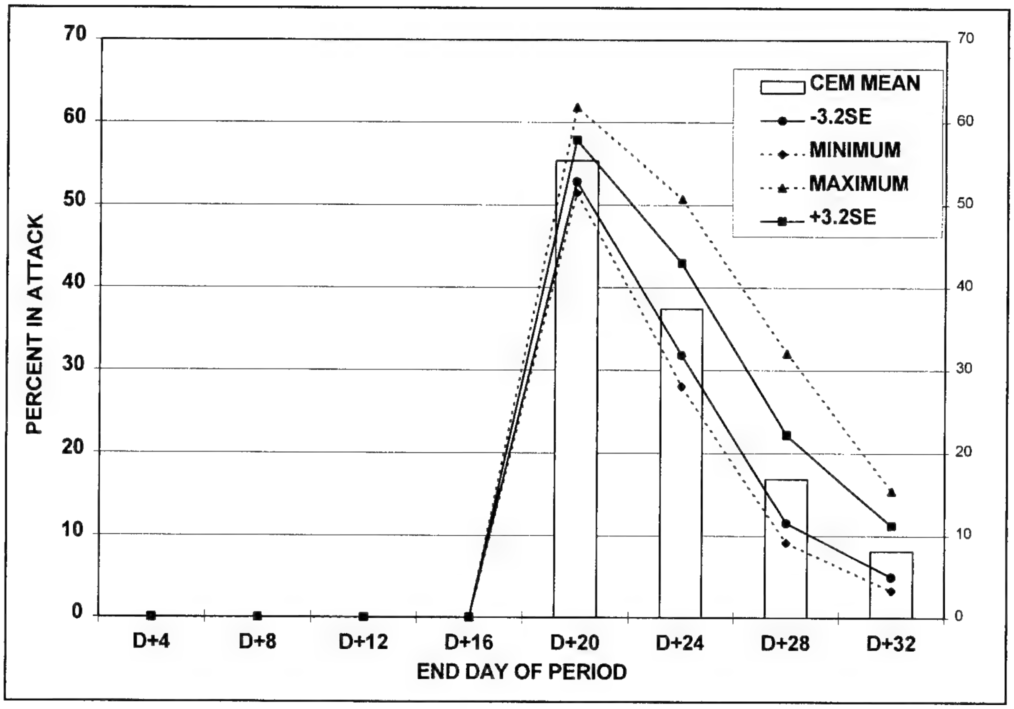


**Figure 6. Percent of US/UK Committed ARCAS Force in Attack Posture during Each 4-day Period**

of uncertainty, moves with more deliberation than is reflected in its combat potential. The STOCEM logic consistently reinforces and exploits success in attack with relentlessly consistent and efficient algorithmic rules, unlike decisions/actions in real life.

It is also possible that the base ARCAS STOCEM move rate inputs are too high because they reflect a potential movement capability not generally achievable in real combat. Actual combat movement is also degraded by tactical, weather, and logistical considerations not explicitly modeled by STOCEM.

*b. Implications on Validity.* The clear configurational similarity of ARCAS FEBA progress to historical FEBA progress in the "bulge" area of the theater at the German "high water mark" of the historical campaign lends support to the credibility of the STOCEM representation of combat and movement. Supplementing this are the similarities between history and ARCAS in average FEBA progress during the first half of the campaign.

*c. Potential STOCEM Logic/Input Changes.* The results showing average ARCAS STOCEM FEBA progress over time reflect a continual movement process which, especially during the attack, does not "pause for breath". The historical FEBA movement in this campaign suggests a sustained rapid force advance punctuated by intervals of reduced mobility and aggressiveness. To better reflect this intermittent progress in STOCEM, a possible model logic improvement is an algorithmic moderation of move rate as a simulated advance gains speed and momentum.

Methods should be investigated which moderate the STOCEM-calculated move rate capability (in selected force postures) in response to a "sufficiently sustained" rapid combat advance. One potential approach is for STOCEM to periodically assess how long a force has been in an attack posture, and to subsequently reduce the STOCEM-calculated move rate as a function of the assessed attack posture duration. Consideration should also be given to reducing the basic STOCEM input move rates in the attack posture in order to reflect degradation not explicitly modeled.

STOCEM logic should be modified so that each unit can be programmed to stop at the user-specified objective positions. In ARCAS

STOCEM, movement past the user-specified force objective occurs during a simulated 12-hour period just before a scheduled end-of period simulation status check. Simulated movement is stopped only when this status check senses attainment of that objective by a unit during that period.

## 8. ANALYSIS OF WEAPON SYSTEM LOSS RESULTS

We now portray and compare the ARCAS STOCEM losses in US/UK tanks, APCs, and artillery systems with historical losses recorded in the ACSDB. Only cumulative losses (destroyed and abandoned systems) are depicted here. Observations impacting on simulation validation, and potential CEM logic modifications which may improve model realism, are subsequently developed from STOCEM/history comparisons. The assessments of model behavior versus history presented herein are derived from, and supported by, both US/UK and German weapon loss results. Comparisons between simulated and historical German weapon losses are summarized at the end of this section. Full results are in the ARCAS study report

## 8.1 WEAPON SYSTEM LOSS COMPARISONS (SIMULATION VS HISTORY)

Figures 7 through 9 compare cumulative ARCAS STOCEM weapon system losses with historical losses, at 4-day intervals, for the US/UK force in the base case scenario. Each chart shows, for the ARCAS STOCEM outcomes, the mean value (light bar), the maximum/minimum bounds (dashed lines) over the replications, and the 90% confidence limit bands (solid lines).

During the first half of the campaign, except for the first four days, ARCAS cumulative US/UK tank loss results, shown in Figure 7, are very similar to historical results and historical losses are contained within the uncertainty bands.

The historical cumulative US/UK tank losses tend to level off as the campaign progresses after its midpoint. ARCAS STOCEM does not exhibit such a tendency until after D+24. Through D + 20, US/UK historical cu-

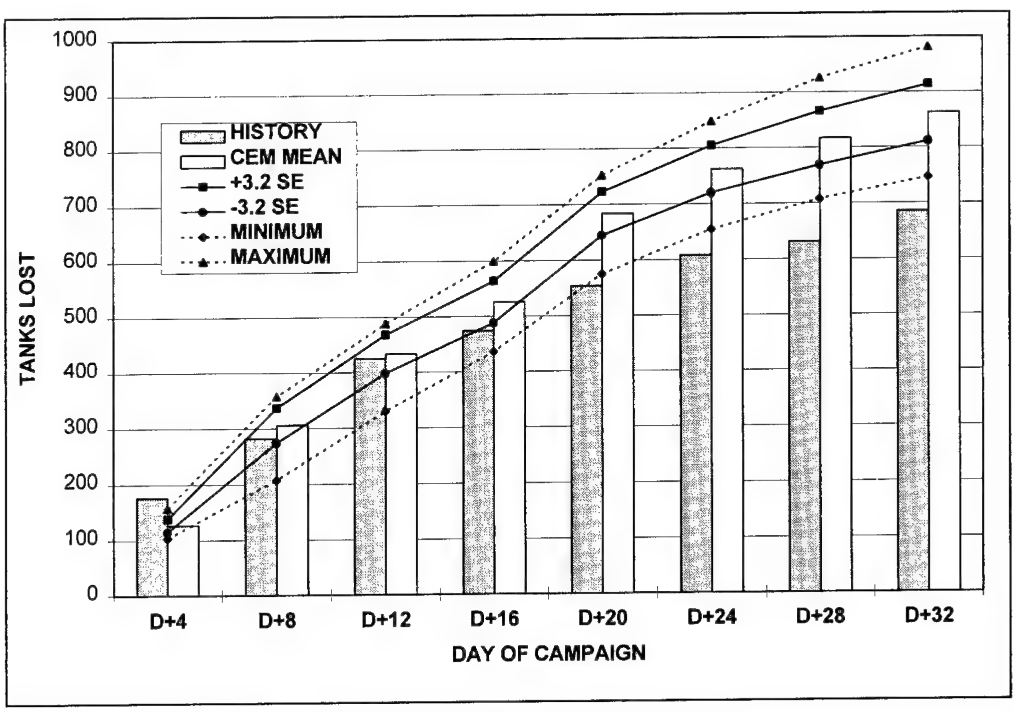


Figure 7. Cumulative US/UK Tank Losses

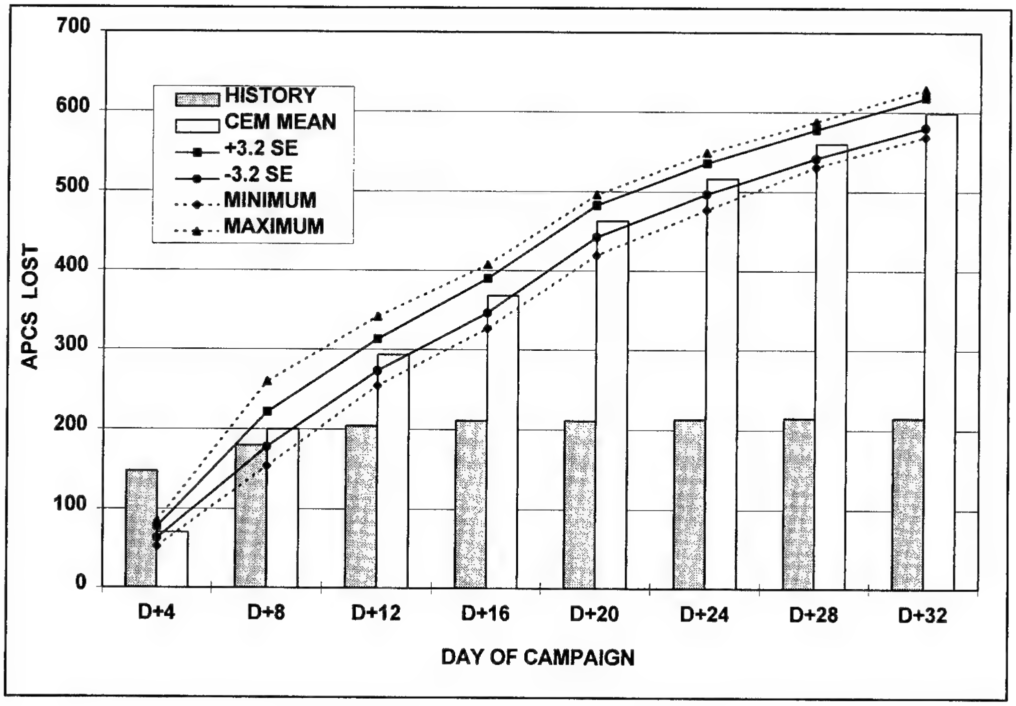


**Figure 8. Cumulative US/UK APC Losses**

mulative kill results are either within the ARCAS STOCEM uncertainty band or are less than 22 tank kills (separation) from the max/min band limits. The out-of-band difference is largest at D + 28, when the ARCAS minimum is 77 kills (12%) in excess of the historical 631 kills recorded through that date.

Figure 8 shows ARCAS STOCEM generating considerably more US/UK losses than occurred in history, especially after D + 4. The historical cumulative US/UK APC losses have a marked tendency to level off, reflecting a zero loss rate, after D + 12. ARCAS does not exhibit any such tendency during the campaign.

Total US/UK APC losses after D + 12 account for 51% of the total US/UK APC kills in ARCAS STOCEM, but only 5% of the total historical kills. Only 2% of historical US/UK APC losses occur after D + 16.

ARCAS STOCEM US/UK artillery losses, shown in Figure 9, are virtually zero, while history shows 195 tubes destroyed or abandoned during the entire campaign. The vast majority of historical artillery losses (86%) occurred before D+12.

## 8.2 ASSESSMENT OF WEAPON SYSTEM LOSS COMPARISONS

*a. Causes of Differences.* For non-artillery weapon losses, ARCAS STOCEM divergence from history tends to be larger in the first few days of the campaign and when the US/UK is counterattacking in the last half of the campaign. These results indicate a tendency for forces modeled in ARCAS STOCEM to lose weapon systems, excepting artillery, at a somewhat faster rate than history, especially when a large part of one force is attacking.

The most plausible explanation for the very low historical US/UK APC losses after D+12 is a cautionary usage policy which conserves mechanized systems, such as the APCs, by reducing their vulnerability and exposure, especially while the force is attacking. This was feasible in the historical campaign since tanks are usually the most forward operating weapon systems and, since the US/UK were on the offensive after D + 16, supporting mechanized

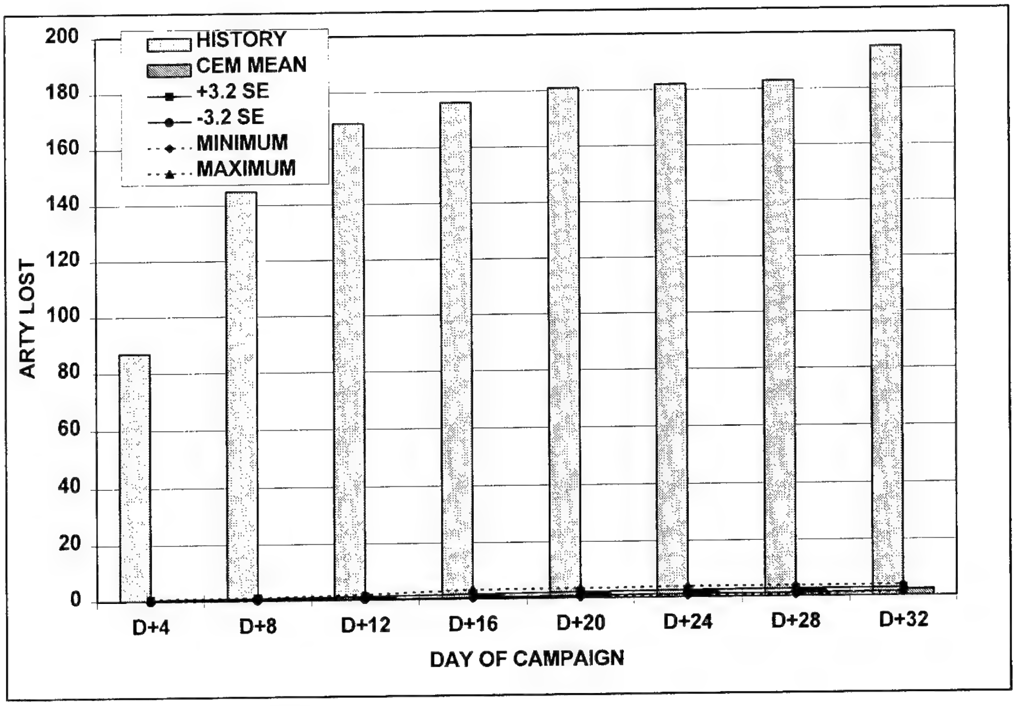


**Figure 9. Cumulative US/UK Artillery Losses**

weapon systems were unlikely to be overrun by a defending enemy.

Vulnerability and exposure of mechanized systems may also have been overestimated, while vulnerability of artillery may have been underestimated.

The occurrence of the vast majority of historical artillery losses during the first twelve days of the campaign indicates that most of these systems were overrun during the initial rapid German advance, which produced a catastrophic breakthrough characterized by speed and surprise. The ARCAS STOCEM losses in this phase are much less because STOCEM does not simulate breakthrough effects. STOCEM combat kills are determined using weapon fires and kill rates as a function of combat posture, but no simulation posture reflects the added speed and surprise of a breakthrough.

*b. Implications on Validity.* ARCAS STOCEM tank losses and APC losses are similar to historical losses during the first half of the campaign. If the catastrophic breakthrough effects of the initial German attack, not modeled in STOCEM, are discounted, then both history and ARCAS STOCEM show negligible US/UK artillery losses. These similarities give support to STOCEM model credibility.

*c. Potential STOCEM Logic/Input Changes.* ARCAS results indicate that, in the "real world", an attacking force may well kill more conservatively, over time, than is reflected in the current STOCEM algorithms. A reduction of an attacking force's basic STOCEM lethality against enemy tanks and APCs appears appropriate, with a higher reduction associated with a higher strength advantage (for the attacker).

Negligible historic US/UK APC and AT/M losses after D + 8 indicate a successful US/UK policy of conserving mechanized systems by reducing their vulnerability and exposure while attacking. Such a policy is apparently not reflected in STOCEM. Methods should be investigated to enable CEM to simulate a "conservative use" policy for a force's mechanized weapon systems. Such a policy will sharply reduce the vulnerability of mechanized systems when favorable attack conditions have been created after a period of heavy losses.

Historical system losses are especially high during the early part of the campaign due to a catastrophic breakthrough, during which an

initially superior and rapidly moving German force attacked, surprised, and overran portions of the US/UK force. Methodology should be investigated which enables STOCEM to simulate a "breakthrough" combat attack posture. A breakthrough attack posture will produce a significant acceleration in defender system attrition, and is related to attacker speed and an overwhelming attacker force advantage.

## 8.3 SUMMARY OF GERMAN WEAPON SYSTEM LOSS COMPARISONS

German weapon losses are similar in trend to the US/UK results described above. Except for artillery, simulated German weapon losses tend to be greater than historical losses. However, unlike the US/UK, the historical German losses are not disproportionately concentrated in the early days, but are relatively evenly distributed throughout the campaign. Synopsized comparisons of cumulative German weapon losses by weapon type include:

*a. Tanks.* Although there is close agreement with history during the first half of the campaign, total simulation kills over the entire campaign are almost double the historical total.

*b. APCs.* Simulation losses are slightly greater than historical losses.

*c. AT/Ms.* Simulation losses are generally three to six times historical losses.

*d. Artillery.* Total simulation losses are about half the total historical losses.

Full descriptions and displays of German results can be found in the ARCAS study report.

## 9. ANALYSIS OF PERSONNEL CASUALTY RESULTS

We now portray and compare the total cumulative ARCAS STOCEM US/UK and German personnel casualties with historical results in the ACSDB. Only cumulative casualties are depicted here. Observations impacting on simulation validation, and areas of investigation for potential CEM logic modifications, which may improve model realism, are subsequently developed from the STOCEM/history comparisons.

## 9.1 PERSONNEL LOSS COMPARISONS (SIMULATION VS HISTORY)

Figure 10 shows ARCAS STOCEM and historical cumulative (since D-Day) total US/UK personnel casualties at 4-day intervals. Figure 11 shows comparable German personnel loss results.

The historical US/UK cumulative casualties appear to be similar to the ARCAS STOCEM averages both in magnitudes and trend (over time). The historical German cumulative casualties appear to be similar to the ARCAS STOCEM averages primarily during the first half of the campaign.

ARCAS STOCEM tends to produce more casualties than actually occurred, and the differences between history and ARCAS STOCEM are larger for German casualties. The largest differences occur for German casualties during the US/UK counterattack in the second half of the campaign. Total cumulative ARCAS STOCEM US/UK casualties during the entire campaign are only slightly (about 12%) larger than historical results, while total cumulative ARCAS STOCEM German casualties are about 44% larger than history.

Figure 12 shows the unweighted arithmetic average fraction of total ARCAS STOCEM and historical US/UK casualties in each casualty category (KIA/WIA/CMIA/DNBI) during the campaign. These averages exclude the period 19-21 December, which had extremely large CMIA due to the encirclement of portions of the US 106th ID during the German breakthrough.

The figure also shows, for both history (points connected by dashed lines) and ARCAS STOCEM (points connected by solid lines), the maximum and minimum over the individual daily casualty fractions, excluding the period of 19-21 December, 1944.

Since the minimum daily value for ARCAS STOCEM KIA and WIA is greater than the maximum of corresponding historical daily values, ARCAS STOCEM consistently overestimates daily KIA and WIA relative to historical casualties. The ARCAS STOCEM average KIA fraction and WIA fraction are almost double the corresponding historical values.

The ARCAS STOCEM mean daily CMIA and DNBI casualties are usually underestimates of historical casualties. The ARCAS

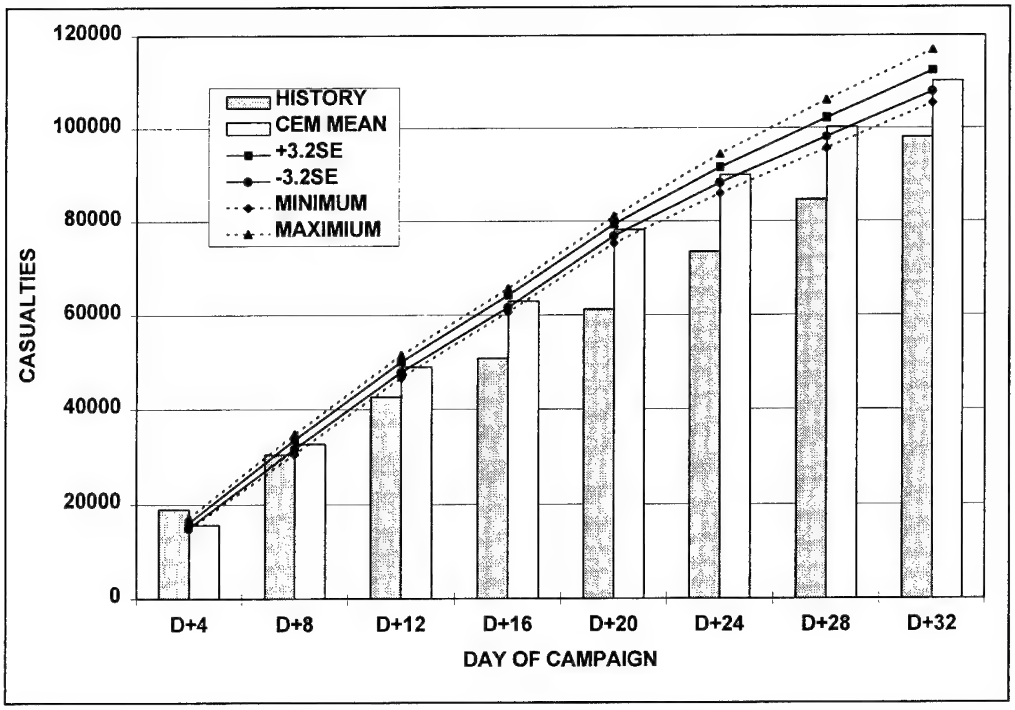


**Figure 10. Cumulative US/UK Personnel Losses**

STOCEM average CMIA fraction is almost a third of the corresponding historical value, while the ARCAS STOCEM average DNBI fraction is almost half of the corresponding historical value.

The day-to-day variation in casualty fraction, as represented by the spread between maximum and minimum, is (proportionately) larger for the historical WIA, CMIA, and DNBI values than for ARCAS STOCEM values.

## 9.2 ASSESSMENT OF PERSONNEL LOSS COMPARISONS

*a. Causes of Differences.* The ARCAS STOCEM German personnel casualty results, in conjunction with the US/UK engagement posture profiles during the simulation, indicate that ARCAS STOCEM generates an excessive number of German casualties when a substantial part of the US/UK force is in attack posture. In the real world, as reflected by history, the attacking US/UK force appears to inflict German casualties at lower rates, over time, than is reflected in the current STOCEM algorithms.

The 4-day periods with the greatest ARCAS STOCEM deviations from history are the periods ending at D + 8, D + 16, and D + 20, when STOCEM generates too many casualties. The period ending at D + 8 is near the peak of the historical German attack, and the US/UK force in ARCAS STOCEM has the largest representation in attack posture during the 4-day period ending at D + 20. These results suggest that ARCAS STOCEM personnel attrition in attack posture is excessive. The overestimation of German casualties is especially large (140%) in the period, ending at D + 20, during the peak of the ARCAS STOCEM US/UK counterattack.

It is also possible that doctrinal differences caused fewer German losses than the weapons lethality would imply.

The breakthrough effect observed in weapon loss results also applies to personnel casualties. The initial phase of the German attack historically produces a much higher number of US/UK KIA and CMIA than the rest of the campaign. The ARCAS STOCEM results do not reflect this.

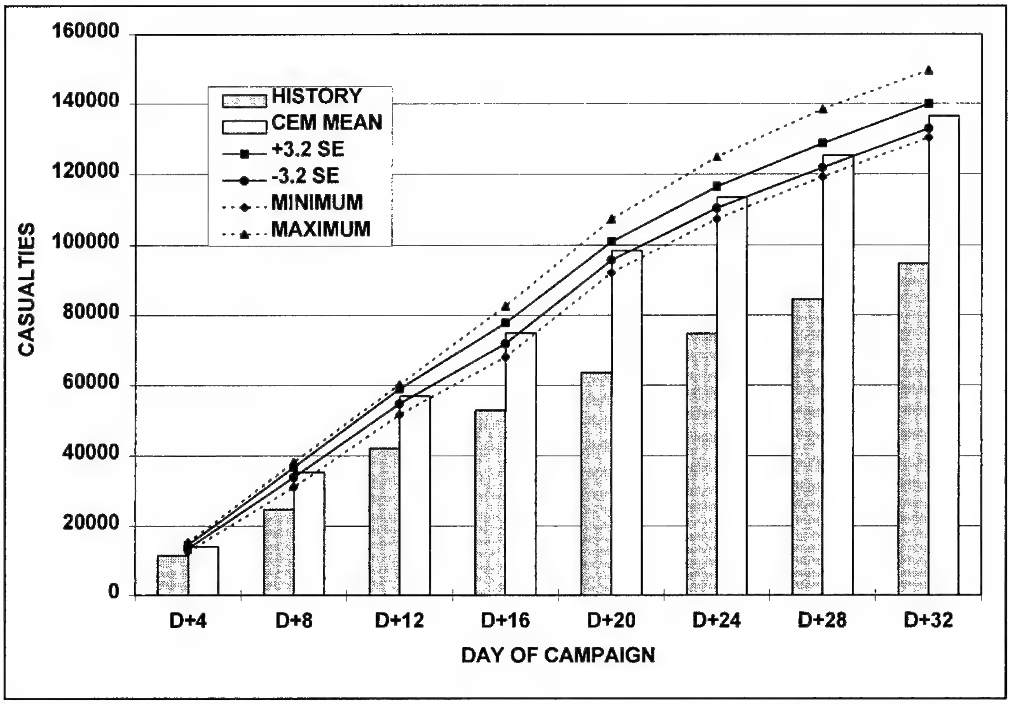


**Figure 11. Cumulative German Personnel Losses**

*b. Implications on Validity.* The similarities between ARCAS STOCEM and history in magnitude and trend of cumulative STOCEM total casualties over time give support to STOCEM credibility. Additional observed trend similarities between STOCEM and history in US/UK DNBI fraction and CMIA fraction also enhance the credibility of the STOCEM combat representation.

*c. Potential STOCEM Logic/Input Changes.* Since ARCAS STOCEM personnel attrition in attack posture may be excessive, a reduction of a STOCEM attacking force's lethality against personnel appears appropriate. Methods should be investigated which reduce an attacking force's basic STOCEM lethality against enemy personnel. Consideration should be given to associating a larger reduction with a higher strength advantage (for the attacker).

Redistribution of STOCEM casualty partitioning process over the four casualty types may be appropriate. The observed differences between historical and ARCAS STOCEM results suggest investigation of revised casualty redistribution rules conforming more closely to history.

Investigation should be done into methods which simulate a "breakthrough" combat attack posture, which generates significantly accelerated defender CMIA, and possibly DNBI, casualties, and which is related to attacker speed and overwhelming attacker force advantage.

Any revised methodology should be able to reflect differences in operational doctrine in each combat posture. This capability is especially important for the simulation of modern forces.

## 10. SUMMARY OF ARCAS RESULTS

Similarities and differences noted in the comparison of ARCAS STOCEM with history, as developed from all results generated in the ARCAS study, are summarized in Table 1. Suggested areas of investigation for STOCEM logic/input modifications are summarized in Table 2. These tables include observations and suggestions based on the full spectrum of ARCAS results, of which only a sample are presented in this paper. The reader is referred to the ARCAS study report for the complete set

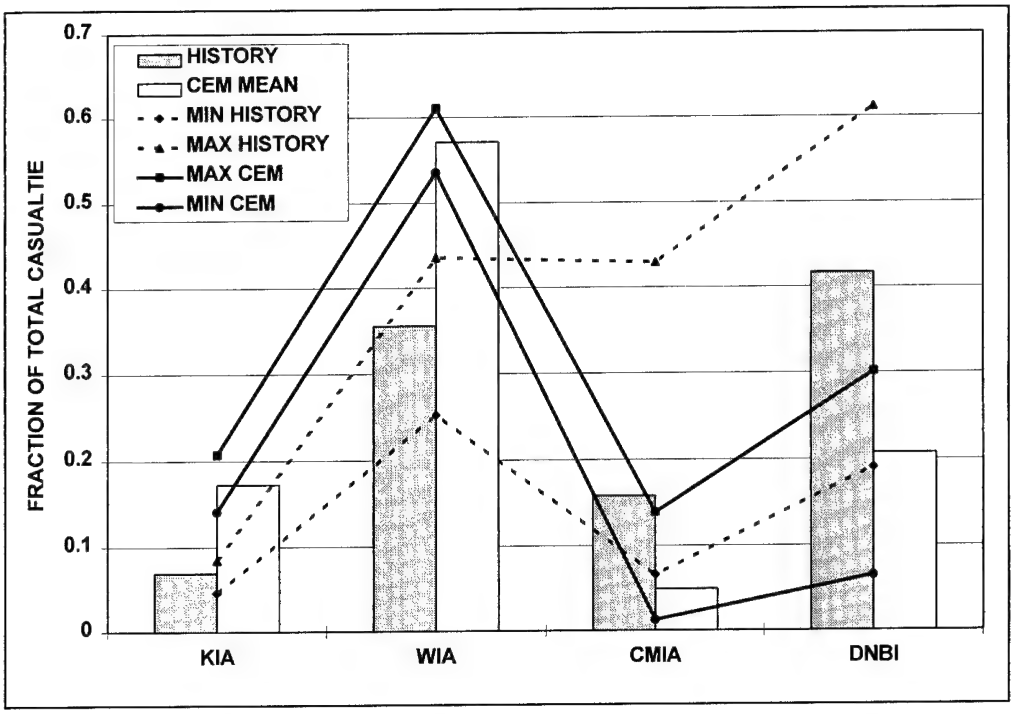


Figure 12. Average Fraction KIA/WIA/CMIA/DNBI in Total US/UK Casualties

Table 1. Summary of ARCAS vs. History Comparisons

| OUTCOME TYPE | SIMILARITIES: ARCAS VS. HISTORY | DIFFERENCES: ARCAS VS. HISTORY |
|---|---|---|
| FEBA progress | (1) Maximum FEBA advance<br>(2) FEBA "bulge" shape | Faster movement in ARCAS |
| Ammo expenditure | US/UK tonnage expended | Much higher German tonnage expended in ARCAS |
| Tank losses | Losses in first 16 days of scenario | Excessive ARCAS losses in last 16 days |
| APC losses | German losses | Excessive ARCAS US/UK losses |
| AT/M losses | | Excessive ARCAS losses |
| Artillery losses | US/UK losses when catastrophic breakthrough effects are discounted | Considerably lower ARCAS losses |
| Personnel lost | (1) US/UK total casualties<br>(2) DNBI & CMIA trends over time | (1) Excessive ARCAS total German casualties<br>(2) Proportion of ARCAS KIA & WIA too large<br>(3) Proportion of ARCAS CMIA and DNBI too low |

**Table 2.** Areas of Investigation for STOCEM Input/Logic Modification

| OUTCOME TYPE | STOCEM INPUT MODIFICATION (ARCAS) | STOCEM LOGIC MODIFICATION |
|---|---|---|
| FEBA | Reduce input move rates of attacker | (1) Reduce move rate after a sustained advance (2) Stop unit movement at a set objective. |
| Ammo expenditure | Revise German single round weight inputs | |
| Weapon system losses | (1) Reduce vulnerability of armor & ATM systems (2) Increase vulnerability of artillery (3) Simulate conservation of mechanized systems when strength is sufficient | (1) Reduce lethality of an attacking force (2) Simulate conservation of mechanized systems when strength is sufficient (3) Simulate "breakthrough" attack posture & attrition. |
| Personnel losses | (1) Reduce vulnerability against an attacking force (2) Change partition of casualties into KIA/WIA/CMIA/DNBI | (1) Reduce lethality of an attacking force (2) Change partition of casualties into KIA/WIA/CMIA/DNBI (3) Simulate "breakthrough" attack posture & casualties. |

of results underpinning the observations in these tables.

## 11. CONCLUDING REMARKS AND FUTURE WORK

The ARCAS study is the first attempt to assess and improve the credibility of a fully automated combat model by simulating a large-scale historical campaign and comparing model outputs with historical outcomes. Key to this analysis were the construction and use of a custom-built detailed historical data base representation of the historical campaign, which was configured to provide inputs to the combat model. Another key element was the use of a stochastic simulation to include and quantitatively represent random variation in model outcomes.

While the resulting report card on comparison of model results versus history is constrained both in specificity and comprehensiveness, the observed similarities and differences provide new and useful insights into behavior of the STOCEM combat simulation. More importantly, the points of difference (between model and history) become pointers to potential model improvements. CAA is using the ARCAS results to develop and test potential modifications in STOCEM which are designed to increase model credibility.

The ARCAS results should be regarded as only a first step in the Model-Test-Model (M-T-M) paradigm of validation methodology which uses model test and evaluation results in an iterative process of successive model improvement with each successive step increasing overall validity. A different historical campaign is a necessary baseline for an operational (re-) test of an improved STOCEM, and can also provide additional insights on simulation behavior and credibility. Without such a test, use of the ARCAS results to "retune" STOCEM begs the question of whether consequent model changes improve prediction in a broader real world scenario context.

The WW II Battle of Kursk is planned as the historical campaign for use in testing and assessing the predictive value of ARCAS-based changes made to STOCEM. CAA is in the early stages of a STOCEM application to the Kursk battle, with objectives analogous to those of ARCAS. A large historical data collection effort has been completed and a data base analogous to the ACSDB has been created. Testing of

STOCEM against history in this battle will also seek guidelines for additional STOCEM improvements.

Since the inputs and factors producing STOCEM results are many and complex, rationales developed from ARCAS results must be regarded as hypotheses which can gain (or lose) support through additional STOCEM excursion cases. Such testing will be done as part of the STOCEM improvement effort.

The ACSDB also can be exploited to derive historical statistics for assessment of combat trends/patterns which can serve as a basis for confirming or refining algorithmic rules commonly used in models of theater combat. For example, relationships between casualty ratios and force ratios can be examined. CAA is undertaking this work as resources permit.

## ENDNOTES

[1] Opinions, interpretations, conclusions, and recommendations are those of the author, and are not necessarily endorsed by the U.S. Army.

[2] The research described herein was sponsored by the U.S. Army Concepts Analysis Agency, and as such is not subject to copyright laws.

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# Finding an Optimal Stationing Policy for the US Army in Europe After the Force Drawdown

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## ABSTRACT

With the continuing reduction of forces in Europe, it is apparent that the base support structure cannot be maintained at current levels. The purpose of this effort is to develop a methodology to assign US Army units remaining in Europe to installations in an economical manner, and to make recommendations regarding which installations are candidates for deactivation and closure. An integer programming model has been formulated which minimizes annual costs subject to constraints on resources, implementation costs, unit proximity, and support requirements. The model can be used to provide decision makers with insights regarding resource utilization and shortfalls, and costs of implementing various stationing plan alternatives. Model development and data collection issues are discussed. Computational experience is given and techniques used to improve model performance are described.

## INTRODUCTION

Since the end of World War II, the US Army has maintained a significant forward-deployed force on the continent of Europe. The principal mission of this force was to deter aggression by the Union of Soviet Socialist Republics, and failing that, defend western Europe from attack until adequate reinforcements arrived to defeat the attackers.

For most of this "Cold War" period, the US Army in Europe consisted of two full army corps, the Fifth and the Seventh Corps, a full logistical support command, the 21st Theater Army Area Command, and numerous other units and organizations that served various functions. Altogether 225,000 soldiers were stationed in Europe during the Cold War period.

In 1990 the Conventional Armed Forces Europe (CFE) Agreement with the Soviet Union was implemented. This agreement signaled the beginning of a drawdown of troop strength in Europe.

The collapse of the Soviet Union in 1991 greatly reduced the perceived threat to the security of western Europe and the national interests of the United States. Consequently, the need to expend nearly one third of the $300 billion U.S. defense budget to maintain such a large European presence was called into question. Reduction in troop strengths were accelerated. Ultimately, the decision was made to leave only 65,000 soldiers stationed in Europe.

The problem remained as to where to station the troops that were left in Europe after this drawdown was complete. It was immediately apparent that the base support structure that existed to station 225,000 troops was no longer necessary for the units that would remain. The locations of these bases correspond largely to where American forces stopped at the end of World War II, so no particular pattern existed that would suggest a stationing plan for the remaining units. Clearly, leaving the units in the locations they were in previously would have been inefficient.

An organization known as the CFE Cell was formed in the headquarters of the US Army in Europe. Its task was to develop a stationing plan. In performing this task, they were directed to consider the following factors: costs (both annual and one-time expenditures), quality of life of the soldiers and their families, and the accomplishment of unit missions. These factors, which are discussed in detail below, were often hard to measure and frequently conflicted; this complicated the development of the plan significantly.

As the drawdown of troops occurred, the CFE Cell developed several stationing plans. Members of the cell made numerous site visits, interviewed hundreds of individuals who were knowledgeable about the various aspects of the stationing requirements, and conducted continuous analysis to arrive at an acceptable policy. This process was both time consuming and manpower intensive.

In order to speed the process of developing stationing plans, and to respond more quickly to ever changing requirements, the US Army Concepts Analysis Agency (CAA) was asked to develop a methodology whose purposes were to produce feasible stationing alternatives, and to evaluate the strengths and weaknesses of these alternatives to facilitate trade-off

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*APPLICATION AREA:*
Resource Analysis, Unit Stationing Forecast

*OR METHODOLOGY:*
Integer Programming

analysis. These alternatives would then serve as "good" starting points for the CFE Cell planning.

In this paper, we describe an integer programming model that serves those purposes. The problem can be characterized as a Facility Location Problem. These problems have been well studied in the operations research literature (see, for example, Nemhauser and Wolsey (1988) or Mirchandini and Francis (1989)).

Our goal was to formulate a model that could be solved using existing and available hardware and software. This goal was well achieved by adopting an integer programming model, to which we applied the branch-and-bound technique with bounds obtained from linear programming relaxations.

In fact, integer programming has proven successful in several analytical efforts to support the drawdown of the US Army. A series of models, similar to the one we propose but smaller in scale, was developed to determine optimal stationing plans for Army units in the continental United States. Dell, et. al. (1994) developed a bi-criteria mixed integer model in which the objective is a weighted combination of operating cost and military worth. Its purpose was to assist the Army in making base closure and realignment recommendations and stationing decisions for maneuver and training bases. Singleton (1991), Tarantino (1992), and Free (1994) describe applications of this model to other aspects of the base closure and realignment process. In the area of personnel reduction during the drawdown, Durso and Donahue (1995) successfully applied a network flow optimization to manage changes in manpower.

In this paper, we describe the integer programming model and the solution method developed. We discuss various aspects of the model-building process including unit and location aggregation, and data collection. In addition, we discuss the techniques which we devised for obtaining good solutions to the model. We conclude with a summary and suggestions for future work.

## MODELING CONSIDERATIONS

As mentioned above, several factors came into play in the development of a stationing plan. In this section we discuss these factors, particularly cost, quality of life, and mission requirements; and establish a basis for our modeling approach.

### Cost Considerations

Through discussions with the study sponsor, we determined that the overriding consideration must be the annual cost of the stationing plan. Since the funds needed to station units at a particular location come from the same appropriation that operating and training funds come from, any savings that are realized can be used to increase the combat readiness of the force. The importance of limiting the expenditure of these funds to a minimum level is paramount. Thus, minimization of annual cost became the objective of the optimization model.

There are two parts to these annual stationing costs that were deemed important to the process of building a stationing plan. They are the overhead cost of having the installation open, regardless of how many units are stationed there, and the cost of stationing the individual units at particular locations. The overhead costs were computed based on historical records. Unit stationing costs were estimated based on the type of unit, the location of the installation and the "cost of living" at that location, distance of the installation from training areas, and the like. Cost estimation was performed in accordance with the US Army Cost Analysis Manual (Department of the Army, 1992b), and use was made of the Force/Organizational Costing System (Department of the Army, 1992a).

Another aspect of the cost of implementing any stationing plan involved the one-time expenditure of funds to physically move units to a different location, as well as to shut down an installation that is no longer needed. These costs are also paid from the operations and maintenance funds of the US Army, Europe and must be constrained.

The first component of these one-time costs is the cost of moving a unit from one location to another when that unit is restationed. This cost is a function of the number of personnel assigned to the unit, the amount of equipment the unit possesses, and the distance from one location to the other. Most of the tactical equipment assigned to the units can be moved by the unit at virtually no cost. However, administrative equipment and the personal property of soldiers and their families have to be moved upon

restationing as well. Local moving companies are contracted to perform this work. Thus the cost of implementing the restationing of units is significant and must be estimated and accounted for in the model.

Another significant component of the one-time costs is the expenditure required to close down installations that are no longer needed. The decision was made several years ago to enter into local long-term utility contracts in order to reduce the operating costs of the installations. At that time the installations had been operating for almost 50 years and there was no reason to believe that the situation would change. In order to break these contracts at installations that are closed, a cost is incurred that must be accounted for in the decision process.

Finally, the cost that is incurred for severance pay to local national employees of the US Army whose services are no longer required must be considered. German law prescribes generous compensation for workers whose jobs are eliminated. Due to the large numbers of German, Polish, and other local national personnel employed at installations across Europe, the cost of this severance pay is potentially very high.

## Quality of Life Issues

The second factor that was to be considered involved the quality of life for the soldiers and their families that remain in Europe. The most economical stationing policy would be likely to have the minimum number of active installations. However, the Commander-in-Chief of the US Army, Europe was concerned that no unnecessary hardship be imposed on the military personnel and their families due to overcrowding. Quality of life standards were established to avoid this situation. For a detailed description of these quality of life standards see Public Affairs Office, US Army Europe and 7th Army (1994). Consequently, adequate housing, schools, medical facilities, commissaries, retail stores, libraries, chapels, recreational facilities, and the like must be provided for any stationing plan to be considered acceptable.

Some of the quality of life considerations can be readily incorporated into a mathematical programming formulation. For example, the requirement for family housing can be related to the number of soldiers. This relation is established by way of usage factors that were derived through the analysis of historical data (see, for example, Department of the Army (1989)). Constraints can then be included to ensure that no unit can be assigned to a location unless an adequate amount of the resource in question, in this case family housing, is available to meet the unit requirement.

Other quality of life standards are not as easily incorporated in the mathematical programming formulation. Instead, they must be handled by examining the options ahead of time to preclude violation of quality of life standards. For instance, the requirement has been established that soldiers should not live further than a 20 minute drive from a library. Almost every installation has access to a library, but a few do not. Rather than attempt to constrain the distance a unit can be located from a library, preprocessing the data to preclude units from being assigned to locations that have no library simplified the problem.

## Mission Requirements

Finally, the stationing of units must be accomplished in such a way as to facilitate the accomplishment of both the combat and peacetime missions of all the Army units in Europe. Mission requirements affect the stationing of units in four ways, namely, the area in which the unit must perform its mission, the locations of the unit's subordinate units and higher headquarters, the locations of supported units, and the sufficiency of resources.

First, units must be located close to their area of operations. During the Cold War, each US Army unit in Europe was assigned a General Defense Position or GDP. The locations of the units' GDP were typically in close proximity to the installations at which the units were stationed, and were oriented eastward. Since the dissolution of the Soviet Union, however, the mission requirements of the units were not so easily stated. Instead of concentrating on a particular GDP, a unit must have the flexibility to respond to a variety of contingencies, including operations outside of Europe. In Operation Desert Storm, for example, Army units from Europe, including the Seventh Corps, were dispatched to the Persian Gulf to participate in the war against Iraq. Thus, a premium was placed on access to road and rail networks, as well as port facilities. Units must be located in places that facilitate their rapid movement.

In order to maintain good command and control, especially among the combat units, subordinate units need to be stationed "near" their headquarters units. From a modeling standpoint, this requirement greatly complicates the problem. We note that in a more conventional location problem, see for example Cornuejols, et. al. (1989), facilities are sited within a given distance from one or more specified locations. Our problem is more complicated because the units must be sited within a certain distance from their superiors units whose locations themselves are also to be determined.

Some units whose mission it is to provide various types of support must be located so that the support can be rendered efficiently and effectively. The classes of support that these units provide include maintenance, supply, personnel administration and finance, transportation, and the like. These units must be located in proximity to the units to which the support must be given. In the case of the transportation units, location decisions are geographically based due to the requirement for transportation throughout Europe. Thus, these units must be centrally located with easy access to the modes of transportation for which they are responsible. Therefore, support units were handled differently in the model than combat units.

For units to be able to perform their assigned missions, sufficient resources must be made available to them. Thus, the assignment of units must be made such that the capacity of the installations with respect to resources is not exceeded. Examples of these resources include maintenance facilities and hardstands to repair and store vehicles and equipment, aircraft operation space for aviation units, and office space for administrative activities.

## Aggregation

The total number of units in the reduced force structure of the US Army in Europe is about 1200. The number of individual installations used by the Army in Europe is about 350. If we establish the decision to be made as the assignment of the units to the installations, in the worst case, the number of binary variables in the integer programming formulation would be the product of these two numbers, i.e. 420,000. In all likelihood, such a model could not be solved using currently available software. Fortunately, a great deal of aggregation that reduces the number of unit-installation combinations is possible and appropriate. The aggregation scheme that was used was consistent with that used by the USAREUR staff in determining the stationing plan manually. We describe this aggregation below.

## Reduction of Units to be Considered

Although the largest proportion of the Army units in question are stationed in Germany, many of the units are located in other European countries, including Italy, Belgium, and Greece. Since there existed no significant plans to move units between countries, each country could be dealt with separately. The methodology developed here can then be applied to each country as needed. For the remainder of this paper, we focus only on the units stationed in Germany.

Many of the 1200 Army units stationed in Europe are small teams or detachments comprising fewer than 10 personnel with very little in terms of vehicles and equipment. As such, these units have negligible resource requirements. Thus, we made the assumption that these units need not be considered explicitly in the model and that they could be assigned to an installation afterward.

Finally, combat units, particularly infantry, armor, cavalry, and artillery units are stationed in such a way that company-sized units belonging to battalions are together on the same installation. Battalions are comprised of three to five company-sized units. Thus, we achieved a significant reduction in the number of units that needed to be considered in the model by assigning battalions, rather than companies, to installations.

When all this aggregation and reduction is complete, about 250 units are left to be stationed in Germany.

## Aggregation of Installations

There are about 350 separate installations that the US Army utilizes in Europe. Ultimately, the decision must be made as to the exact locations to which the various units are assigned. However very few, if any, of the in-

stallations themselves contain sufficient resources to support any unit. The installations have historically been grouped into a system of Military Communities. Together the grouped installations provide the needed resources for the tenant units.

For example, the Wuerzburg Community, composed of several separate installations, is the home of the Headquarters of the Third Infantry Division. Some of the installations are made up entirely of military housing. Others contain office, operations, and maintenance space. Still others are made up of administrative space, aircraft operation space, or vehicle hardstands. None of the separate installations would be adequate to support the stationing of any of the divisional units, but together they supply sufficient resources.

Thus, the decision was made to aggregate the installations at the community level; we used the organization of the installations into communities, called Base Support Battalions (BSBs), for this study effort. This decision was consistent with the procedures used by the staff planners. The resources provided by the individual installations are summed over the entire BSB and these aggregate resources are used to constrain the assignment of units. The final decision regarding the disposition of the units in the communities should be made locally.

The above aggregation reduces the number of locations in Germany to which units may be assigned to about 25.

## Other Limitations on Unit Assignment

The decision had been made that the two divisions remaining in Germany, the 1st Armored Division and the 3rd Infantry Division, would occupy different subsets of the available locations. The partitioning of Germany had already been accomplished, although the detailed unit by unit assignments had not been made. All unit-BSB combinations that did not adhere to this partitioning plan were eliminated from consideration. Similar limitations were made for other units whose location was limited by some other factor that could be identified. Figure 1 shows the BSBs under consideration and the partitioning of Germany.

There was no need to consider assignment of units to BSBs with insufficient resources to meet the units' needs. By preprocessing we can identify those BSBs at which a unit cannot be stationed due to inadequate resources. Any unit-BSB combination that fits into this category was eliminated from consideration. In

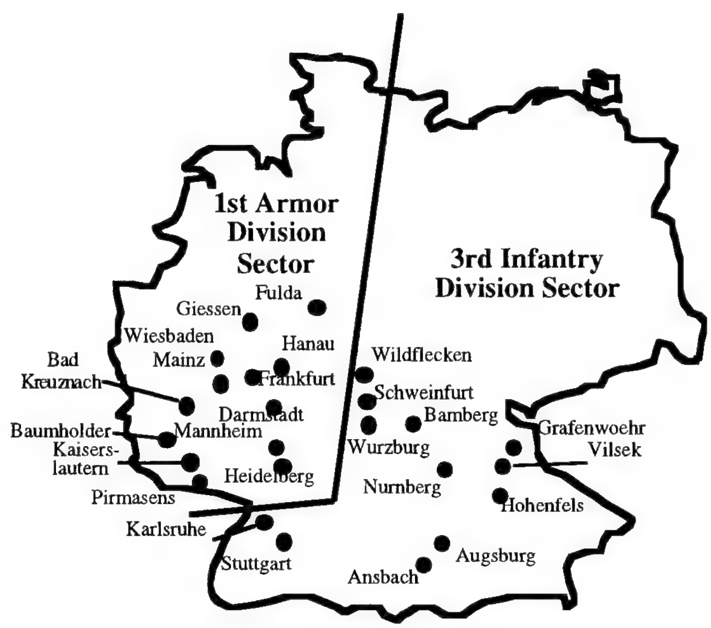


**Figure 1.** BSBs and Partitioning

practice, we observed that between 400 and 500 such unit-BSB combinations were eliminated in this fashion, significantly reducing the size of the problem.

## PROBLEM FORMULATION

The formulation can be summarized as follows:

$$\textit{Minimize}: \sum_{\text{all units}} \left( \sum_{\text{all open locations}} (\text{assigned unit stationing cost}) \right) + \sum_{\text{all open locations}} (\text{location overhead cost})$$

Subject to:

Units have sufficient resources at their designated locations,

Resource capacities at the open locations are not exceeded,

Budget for one-time costs is not exceeded,

Units are located within the required proximity of other units.

In this section, we describe in detail the formulation of the mathematical programming model developed for this analysis.

### Decision Variables

For each unit $i$, we define the set $S_i$ to be the set of BSBs to which $i$ may be assigned. The decision variables are binary and are defined as:

$$x_{ij} = \begin{cases} 1, \text{ if unit } i \text{ is stationed at BSB } j, \\ 0, \text{ otherwise,} \end{cases}$$

$$\text{for } i = 1, \ldots, I, \text{ and } j \in S_i, \text{ and}$$

$$z_j = \begin{cases} 1, \text{ if BSB } j \text{ is open,} \\ 0, \text{ otherwise,} \end{cases} \quad \text{for } j = 1, \ldots, J,$$

where the number of units is denoted by $I$ and $J$ is the number of BSBs. Recall that no unit assignment is allowed to BSBs that lack sufficient resources to support it. Thus, as a preprocessing step, no $x_{ij}$ variables are created for unit-BSB combinations with insufficient resources. This preprocessing includes shared resources which are described below.

### Objective Function

The objective of the optimization is then written as

$$\text{Minimize:} \sum_{i=1}^{I} \sum_{j \in S_i} c_{ij} x_{ij} + \sum_{j=1}^{J} f_j z_i. \tag{1}$$

As discussed above, the objective is to develop a stationing plan that keeps the annual expenditures to a minimum, thus freeing up funds for training, operations, and maintenance. Annual costs that are to be minimized in the objective function are defined as follows: $c_{ij}$ is the cost of stationing unit $i$ at location $j$, and $f_j$ is the annual fixed cost of having BSB $j$ open.

### Basic Constraints

The investment of funds for the purpose of plan implementation is also important. These funds are limited and are constrained by:

$$\sum_{i=1}^{I} \sum_{j \in S_i} m_{ij} x_{ij} + \sum_{j=1}^{J} g_j (1 - z_j) \leq B, \tag{2}$$

where $m_{ij}$ is the cost of moving unit $i$ to location $j$, $g_j$ is the cost of closing location $j$, and $B$ is the budget for one-time costs. Note that we assess the close-down costs for any BSB that is recommended for closure using the complement of the binary variable that indicates whether or not the BSB is open.

To ensure that all units are assigned to one and only one allowable BSB, we introduce the standard assignment constraints

$$\sum_{j \in S_i} x_{ij} = 1, \; i = 1, \ldots, I. \tag{3}$$

To ensure that a BSB is open whenever a unit is assigned to it, we use the constraints:

$$z_j - x_{ij} \geq 0, \; i = 1, \ldots, I, \; j \in S_i. \tag{4}$$

In practice, thousands of these constraints exist and, if included explicitly in the formulation,

would significantly slow the solution procedure. Later we discuss the manipulation of these constraints to reduce run-time of the optimization.

To ensure that units are assigned to BSBs in such a way that their resource requirements are met, and that the resource capacities of the locations are not exceeded, we introduce constraints:

$$\sum_{i=1}^{I} r_{ik}x_{ij} \leq R_{jk}, j = 1, \ldots, J, k = 1, \ldots, K. \quad (5)$$

The amount of resource $k$ available at BSB $j$ is denoted by $R_{jk}$ and the amount of resource $k$ required by unit $i$ is denoted by $r_{ik}$. $K$ is the number of different resource types.

## Shared Resource Constraints

In addition to the resources available at each BSB, there are also resources which are shared by several BSBs. For example, there are three hospitals used by the forces in Germany, so the BSBs are partitioned into three sets (one for each hospital) and every unit stationed at some BSB in the set is served by the corresponding hospital for that set. Aircraft operations space is another resource with this characteristic.

To model this kind of resource usage, we use the following definitions. Let $L$ be the number of shared resources, let $N_l$ be the set of units that use resource $l$, let $\hat{r}_{il}$ denote the amount of shared resource $l$ consumed by unit $i$, and let $\hat{R}_l$ be the available capacity of shared resource $l$. For each shared resource $l$, let $G_l$ denote the set of BSBs served by $l$. For each resource $l$ we have the following constraint:

$$\sum_{i=1}^{I} \sum_{j \in G_l} \hat{r}_{il}x_{ij} \leq \hat{R}_l, \, l = 1, \ldots, L. \quad (6)$$

Although shared resources are utilized by several BSBs, they may actually be located at a particular one. If this is the case, we must ensure that the attached BSB is open whenever some of the shared resource is used. This is achieved as follows: Let the subscript $j(l)$ denote the BSB to which shared resource $l$ is attached. Then if *any* of shared resource $l$ is used, BSB $j(l)$ must be open. This is modeled by the constraint:

$$z_j(l) - x_{ij} \geq 0, i \in N_l, j \in G_l, l = 1, \ldots, L. \quad (7)$$

## Unit Proximity

As mentioned above, units must be stationed within some prescribed distance from other related units. For example, all the infantry battalions in a brigade should be stationed at a location that is relatively close to their brigade headquarters, in order to maintain good command and control. Thus, a unit's location is constrained by the location of the units to which it is a subordinate.

We can model these proximity constraints as follows. Let $P_i$ be the set of subordinate units of unit $i^*$, and let $H_{i^*j^*}$ be the set of BSBs to which subordinates of unit $i^*$ can be stationed, if unit $i^*$ itself is stationed at BSB $j^*$. Thus, we know that if $x_{i^*j^*} = 1$, then for $i \in P_{i^*}$, $x_{ij} = 1$ only if $j \in H_{i^*j^*}$. This can be modeled by the following constraints:

$$\sum_{j \in H_{i^*j^*}} x_{ij} - x_{i^*j^*} \geq 0, \forall i \in P_{i^*}, \forall i^*, j^*. \quad (8)$$

The sets needed in (8) must be determined, for any given problem instance, prior to solution. This determination is based on the distance allowed between the location of a unit and its subordinates; if subordinates of unit $i^*$ must be stationed within some distance, say $d_{i^*}$, of $i^*$ then $H_{i^*j^*}$ is the set of BSBs within distance $d_{i^*}$ of BSB $j^*$.

## Modeling Support Units

Many of the support units, such as personnel administration units, finance units, maintenance units, supply units, and transportation units, particularly those that are assigned to Army divisions, are not associated organizationally with any other units. Rather, these logistical units render support on an area basis, often far from their controlling headquarters, providing service to all units in their area of responsibility. Also, these logistical units must be stationed at a BSB such that their ability to provide support is not exceeded by the logistical requirements of units in their area. Clearly, the representation of these support units in the

model had to be different from that of the combat units given above.

Staff planners typically make the stationing decisions for the divisional units first, and then the headquarters controlling the support units are asked to identify a stationing plan for themselves such that the units whose locations are already specified are adequately supported. Conflicts that arise among the separate stationing plans submitted by the individual support units are then resolved by the staff. The process seemed straightforward, and we originally believed that the operational considerations could be represented mathematically and included in the formulation. Unfortunately, the criteria governing the stationing plans were complex and seemed to involve expert judgments in a way that made mathematical modeling of those criteria impractical.

Consequently, we used a heuristic approach for support units. A partition of the BSBs was determined in a preprocessing step for each of the categories of support. This partition was based upon the capacities of the BSBs to contain the commodity relevant to the category of support under consideration. For example, units in the 266th Theater Finance Command (TFC) provide support based on the number of military personnel stationed at the various BSBs that it supports. Thus, an estimate of the requirement for support at a BSB can be made based on the capacity at that BSB of the critical commodity or commodities.

We implement this approach within the framework of the above formulation by determining the set of allowable locations, $S_i$, for each support unit $i$ so that the sets $S_i$ for all units $i$ of a given type form a partition of the set of all BSBs. These restrictions on the locations of the supporting units are implemented using (4) above. Figure 2 depicts a partitioning of the BSBs for the subordinate finance units (FI) of the 266th TFC.

This approach requires not only a considerable preprocessing effort but a postprocessing effort as well. The solution must be examined to ensure that the set of BSBs that are active in the solution are distributed such that no subset of the partition has too large or too small a requirement for support. If so, a new partition must be developed and the model must be rerun. In the worst case, several iterations might be required to obtain a stationing policy in which the support requirements are met. Fortunately, in practice this problem did not arise, and no additional iterations were needed. For example, a comparison between the computed stationing plan for the 266th TFC and one developed by staff planners reveals that, although the plans were slightly different, the finance units were capable of rendering sufficient support in both.

## Formulation Summary

Using the notation introduced above, the formulation is written as:

$$\text{Minimize:} \sum_{i=1}^{I} \sum_{j \in S_i} c_{ij} s_{ij} + \sum_{j=1}^{J} f_j z_j. \tag{1}$$

Subject to:

$$\sum_{i=1}^{I} \sum_{j \in S_i} m_{ij} x_{ij} + \sum_{j=1}^{J} g_j (1 - z_j) \le B, \tag{2}$$

$$\sum_{j \in S_i} x_{ij} = 1, \; i = 1, \ldots, I, \tag{3}$$

$$z_j - x_{ij} \ge 0, \; i = 1, \ldots, I, \; j \in S_i, \tag{4}$$

$$\sum_{i=1}^{I} r_{ik} x_{ij} \le R_{jk}, \; j = 1, \ldots, J, \; k = 1, \ldots, K, \tag{5}$$

$$\sum_{i=1}^{I} \sum_{j \in G_l} \hat{r}_{il} x_{ij} \le \hat{R}_l, \; l = 1, \ldots, L, \tag{6}$$

$$z_{j(l)} - x_{ij} \ge 0, \; i \in N_l, \; j \in G_l, \; l = 1, \ldots, L, \tag{7}$$

$$\sum_{j \in H_{i^*j^*}} x_{ij} - x_{i^*j^*} \ge 0, \; \forall i \in P_{i^*}, \; \forall i^*, j^*, \tag{8}$$

$$x_{ij}, z_j \in \{0, 1\}.$$

Issues involved in the implementation of this model are discussed in the next section.

# IMPLEMENTATION

This implementation was accomplished using the Mixed Integer Optimizer (MINTO) (Nemhauser, et al, 1994). This software provides a front end for a modern simplex code such as OSL or CPLEX (CPLEX Optimization,

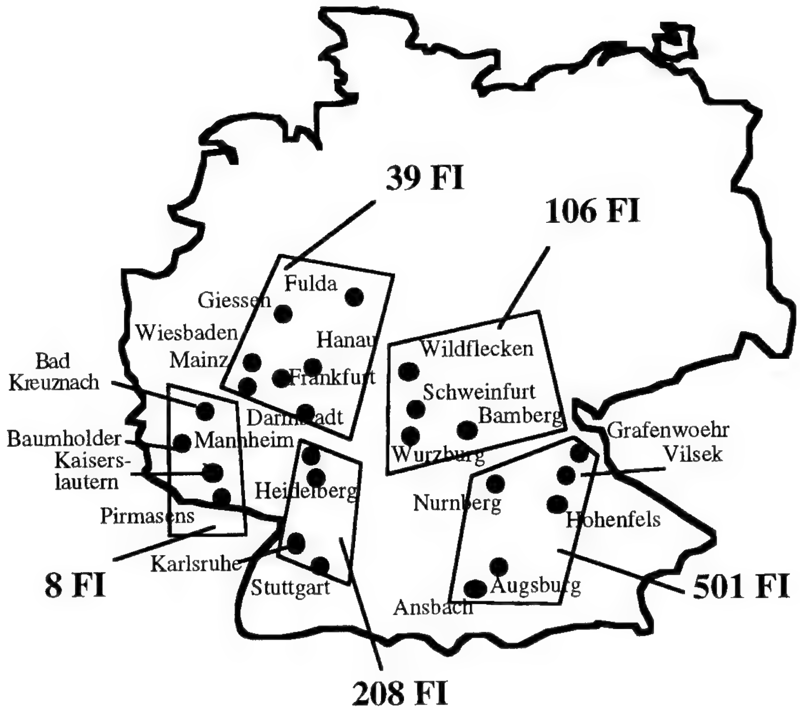


**Figure 2.** Partition for 266th TFC

1990), and facilitates the easy modification of the formulation, allowing alterations to the branching rules, addition of new constraints, and the like.

Below we discuss issues that we confronted in implementing the model.

## Constraint Aggregation

Typically, the first step in solving an integer program involves solving the linear programing problem with the integrality constraints relaxed. The purpose of constraint aggregation is to speed up solution of this LP relaxation without losing any relevant information. Three of the constraint classes defined above are candidates for aggregation, since they may yield a large number of constraints. There are as many constraints (4) as there are $x_{ij}$ variables, which is a very large number. There may also be many constraints (7) in the case that there are many shared resources, or if the set of BSBs served by shared resources is large, or if there are many units which require shared resources. Similarly, if the number of headquarters units, or the number of subordinate units of each parent is large, then the unit proximity constraints (8) will be numerous. Fortunately, we can replace (4) by:

$$\sum_{i=1}^{I} x_{ij} - Iz_i \leq 0, j = 1, \ldots, J, \tag{9}$$

replace (7) by

$$z_{j(l)} - \frac{1}{|N_l|} \sum_{i \in N_l} \sum_{j \in G_l} x_{ij} \geq 0, l = 1, \ldots, L, \tag{10}$$

and replace (8) by

$$\sum_{u \in P_{i^*}} \sum_{v \in H_{i^*j^*}} x_{uv} - |P_{i^*}| x_{i^*j^*} \geq 0, \forall i^*, j^*, \tag{11}$$

and still obtain a valid formulation with many fewer constraints.

The disaggregated constraints (4), (7), and (8) can be viewed as valid inequalities for the smaller formulation. Each time an LP relaxation of the model is solved, the solution can be checked for violations of these valid inequalities. If violated inequalities are found, they are added to the model, and the LP resolved.

Although all aggregations could be useful, the number of shared resources was found to be very small, and the number of headquarters units was small, with each having few subordinate units. So, aggregations of (7) and (8) did not significantly improve performance. However, the aggregation of (4) into (9) was found to be crucial to solving the problem efficiently.

We emphasize that even though our implemented formulation uses (9) and not (4), the LP we solve at each node *is* the so-called "tight" formulation in which all the constraints (4) hold. We add constraints of type (4) to the LP only if they are found to be violated, and so gain the advantage of the "tight" bound without the inefficiency of including *all* of constraints (4) in the formulation.

## Branching

The model we have formulated clearly encapsulates three levels of decision making. At the top level, we have the decision of whether or not a BSB is to remain open or be closed. Then we have the decision of where a headquarters unit is to be stationed. At the bottom level, we must decide where subordinate units are to be located. Decisions made at the top two levels restrict the options available at the levels below. This fact provided us with the motivation to use branching priorities. Specifically, we request that variables which model the decision to open or close a BSB, the $z_j$ variables, become integer before other variables are branched on. We place the second priority on the $x_{ij}$ variables where unit $i$ is a headquarters unit. These priorities reflect the relative levels of impact of the different decisions on later decisions. The use of this prioritization scheme did not by itself sufficiently improve performance.

In addition to the three-level prioritization of variables for branching, we considered a branching rule different from the usual binary dichotomy. Within each of the lower two priority classes (those for unit assignment variables) we use a special ordered set branching rule, and prioritize the assignment of each unit based on that. For each unit $i$, we have the assignment constraint $\Sigma_{j \in S_i} x_{ij} = 1$. Let $\hat{\mathbf{x}}$ denote the current LP solution. If $\hat{x}_{ij}$ is fractional for some $j$, then we determine a set $S_i(\hat{x}) \subset S_i$, $S_i(\hat{x}) \neq \emptyset$, with the property that $\Sigma_{j \in S_i(\hat{x})} \hat{x}_{ij}$ is fractional, and branch on the dichotomy that either $\Sigma_{j \in S_i(\hat{x})} \hat{x}_{ij} = 1$ or $\Sigma_{j \in S_i \setminus S_i(\hat{x})} \hat{x}_{ij} = 1$.

We gave careful consideration to how $S_i(\hat{x})$ should be chosen for each unit $i$, and also to which unit in a given priority class should be selected for branching. The average cost paid in the LP solution $\hat{x}$ to locate unit $i$ is $w_i(\hat{\mathbf{x}}) = \Sigma_{j \in S_i} c_{ij}\hat{x}_{ij}$. A critical decision is whether the BSB to which unit $i$ is assigned will cost more, or less, than the average. Our branching rule reflects this decision: for each unit $i \in F(\hat{\mathbf{x}})$ we define

$$S_i(\hat{\mathbf{x}}) = \{j' | c_{ij'} \leq w_i(\hat{\mathbf{x}})\},$$

where $F(\hat{\mathbf{x}})$ denotes the set of units $i$ for which $\hat{x}_{ij}$ is fractional for some $j \in S_i$.

At any given node of the branch-and-bound tree, we must decide which unit we will use for branching. We choose to generate a branch from the set constraint for unit $i$ with the largest relative cost difference across the division (indicated by $S_i(\hat{\mathbf{x}})$). Thus, our selection criterion is to branch on the set constraint for the unit $i^*$ which solves

$$\max_{i \in F(\hat{\mathbf{x}})} \left( \min_{j \in S_i \setminus S_i(\hat{\mathbf{x}})} c_{ij} - \max_{j \in S_i(\hat{\mathbf{x}})} c_{ij} \right)$$

Because of the way $S_i(\hat{\mathbf{x}})$ is formed, this difference is guarenteed to be positive. Then given $i^*$, we branch on the dichotomy described above using $S_i^*(\hat{\mathbf{x}})$.

## Variable Fixing

Despite our efforts to develop a good formulation and effective branching rules, we encountered a great deal of difficulty in determining a good integer solution for the largest problem. Without a good integer solution, the number of active nodes in the branch-and-bound tree grows rapidly. The result is that all available memory is consumed before a near-optimal solution is found. The key to obtaining a good integer solution proved to be variable fixing: given some tolerance $\epsilon > 0$, and an LP-optimal solution $\hat{\mathbf{x}}$, for any unit $i$ and any BSB $j \in S_i$ with $\hat{x}_{ij} > 1 - \epsilon$, we add the equality $x_{ij} = 1$. We effectively fix variables whose values are close to 1 for the remainder of the procedure. After experimentation, we set $\epsilon = 0.01$, and after searching nine nodes of the branch-and-bound tree, found an integer solution having cost within 3.0% of the cost of the LP solution at the root node, i.e., within 3.0% of optimal.

Once we had obtained a good integer solution using variable fixing, we ran the optimiza-

tion procedure again, this time *without* the variable fixing. However, we did use the bound we obtained from variable fixing to reduce the number of nodes that needed to be explored. After searching fewer than 1000 nodes, this strategy yielded a better integer solution, having a gap of 1.7% from the LP solution.

## RESULTS AND CONCLUSIONS

During the conduct of this study effort, many excursions were performed using several versions of the input data set. Results were given to the study sponsor who provided feedback, updated data, and guidance with respect to decisions that were already made for incorporation into the model. In this section, we discuss the results achieved including both the computational experience and cost results. Due to the sensitivity of the of the decision process, we omit actual unit-location results. We conclude with some observations and suggestions for future work.

### Computational Experience

From the very beginning, this problem proved to be computationally challenging. Early experimental runs took days to produce feasible integer solutions. As a result of the modifications made to the formulation and the use of the other techniques described above, the time required to obtain a good solution was reduced to 4-5 hours of computer time.

A typical problem that we solved using the above formulation and techniques had 1330 integer variables and 450 (aggregated) constraints. Approximately 1300 constraints of type (3) discussed above were added during the solution process. There were approximately 16,500 non-zeroes in the original constraint matrix. All computation was performed on an IBM RS 6000 model 500 series, using the MINTO software linked to the Optimization Subroutine Library (OSL) (IBM Corporation, 1990).

### Cost Results

A typical run of the model produces several feasible integer solutions representing different stationing plans, each one better than the last with respect to the objective. The examination of these solutions gives insight into the tradeoff involved in making the stationing decision. These alternate plans can be shown to the decision makers so they get a better idea of their range of options.

Figure 3 shows the cost results for four alternative solutions to the largest problem and compares them with that of the staff solution which was produced by the CFE Cell. The costs

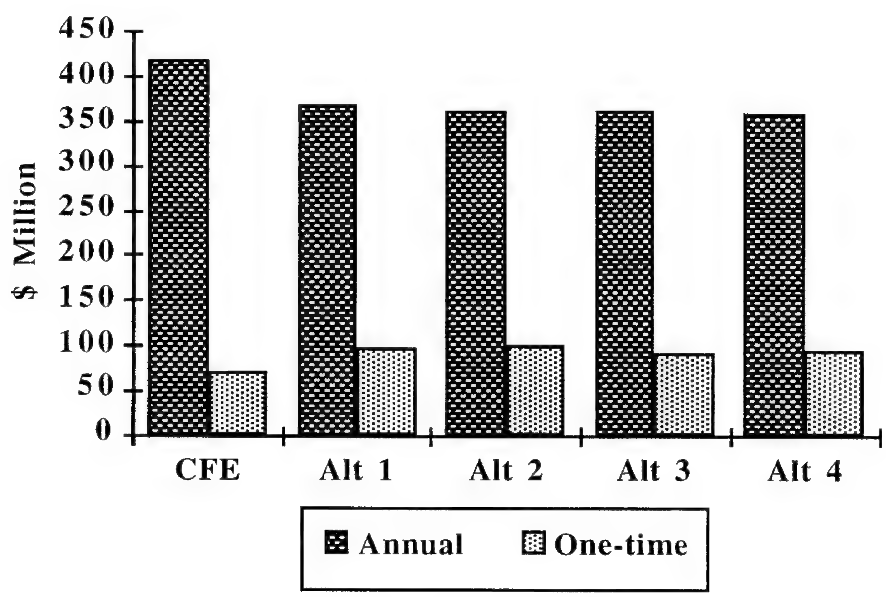


**Figure 3.** Resulting Costs

associated with the CFE Cell solution were $418 million annual cost, with a one-time cost of $70 million. We note that the annual cost savings were $49 million, $55 million, $56 million, and $58 million for alternatives 1 through 4, respectively. To achieve these savings, however, additional investment was needed to implement the alternative plans: $28 million for alternative 1, $31 million for alternative 2, $21 million for alternative 3, and $25 million for alternative 4.

The most important difference between the CFE Cell solution and the four alternatives generated by the model is that fewer BSBs remain open in the alternative plans. Thus, the overhead costs of having extra BSBs are avoided, but additional investment costs are incurred to shut down the unneeded BSB. In all of the above alternatives, $69 million in one-time costs is needed to pay for BSB closure. On the surface, alternative 4 seems best since it has the lowest annual cost, coupled with the second lowest one-time cost. However, some other factor, perhaps some political consideration, might override these apparent benefits in the eyes of the decision maker, and make some other alternative more attractive.

## Observations

We have demonstrated the ability of our solution procedure to produce feasible and reasonable alternative stationing plans fairly rapidly. Results from the model presented in this paper have been given to the decision makers in the US Army Europe staff to be used in their decision process. In general, we found that additional investment was necessary to achieve a reduced annual cost of stationing. Although this result is not surprising, this methodology provides an analytical tool for evaluating this tradeoff, and for providing justification for additional investment funds. The model is available for use in the next round of force reductions whenever they occur.

The methodology presented here could be useful beyond the stationing of forces in the European theater of operations. It is being considered for use in other theaters, and for providing analytical support for the Army in the implementation of Base Realignment and Closure Commission decisions in the continental United States. These issues are always emotional and contentious, and objective analysis is needed in the decision process.

## Future Research

Three areas may provide opportunities for additional research. The first is the speed of the solution process. The faster the model solves, the more information can be provided to the decision makers. Second, the problem of stationing of units within a BSB needs to be addressed. Finally, alternative approaches, such as those using decomposition schemes, may be considered.

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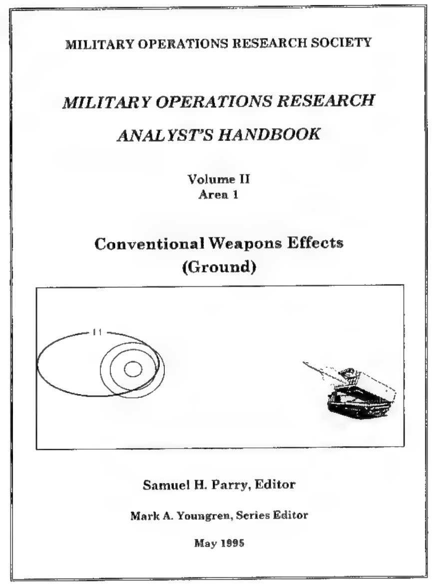
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Volume II
Area 1

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**(Ground)**

Samuel H. Parry, Editor
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May 1995

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# Consolidating the USAF's Conventional Munitions Models

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## INTRODUCTION: THE MUNITIONS OPTIMIZATION PROBLEM

The general problem the US Air Force faces when procuring and managing conventional aircraft munitions is determining the best mix of weapons to hold in inventory. The desire to determine the best inventory 190 along with the structure of the problem—led the Air Force to adopt optimization over 25 years ago as a means to determine munitions stocks.

However, the Air Force's experience has shown there is a more specific set of problem definitions, with the following three covering virtually all questions a munitions optimization must answer: first, what is the effect of having or not having a particular weapon in the inventory (*tradeoffs*); second; what is the best way to allocate munitions and aircraft to targets, given a fixed inventory and scenario (*allocations*); and third, what weapons inventories do we need to meet our warfighting goals for a particular scenario (*requirements*).

Over the years the Air Force has built a set of models to address these problems, all of which require certain fundamental inputs. First, the models need a *scenario,* which consists of a collection of target types of various quantities and some measure of importance or precedence for their destruction. Second, the models require a set of aircraft, which fly time-varying *sortie rates* (missions per aircraft per day). Third, the models need data describing the *effectiveness* of each feasible aircraft-weapon combination against each target type. Given this information, these models try to optimize the allocation of aircraft sorties and weapons against targets in accordance with some objective function.

The Air Force has a common approach to the munitions problem: use optimization to best allocate aircraft and weapons to targets in a particular scenario. However, the objective functions and constraints of the existing models differ significantly. There is no general agreement among the models on what the meaning of "best" is, nor is there much agreement on which constraints are necessary.

Before proceeding, it will be helpful to discuss the dimensions of the entities in this class of models (Figure 1). *Sorties* are valid combinations of an aircraft, weapon, weapons loadout, delivery tactic (or profile), time period, weather state, target, and target depth (or distance band). *Targets* are classified by type, distribution across distance bands, and target class. *Weapons* are characterized by type, component family (for weapons that share common parts), and qualification requirements (for weapons that can only be employed by a limited proportion of aircraft or aircrews). The existing models use these dimensions in varying degrees.

## THE EXISTING MODELS: HEAVY ATTACK, TAM, MIXMASTER, AND CTEM

At this point, it is useful to provide a brief overview of the three existing models included in the consolidation (HEAVY ATTACK, TAM, MIXMASTER) and another widely-used model in the same class (CTEM). Figure 2 contains a summary of the differences; a complete discussion and specific references are available in Yost [1995].

HEAVY ATTACK is the oldest of the models, having been in use since 1973. The model was originally formulated by analysts in the Office of the Secretary of Defense and was implemented by RAND (Clausen [1974], Brown [1994]). HEAVY ATTACK assigns values to each target and optimizes the total target value destroyed (TVD). The model uses a nonlinear objective function to capture battle-damage assessment (BDA) effects and diminishing marginal returns, and optimizes for a single period; the latter is called the *time-myopic* approach. HEAVY ATTACK is the most aggregated of the three models, allocating aircraft sorties to targets without directly modeling weapons. Instead, HEAVY ATTACK determines the best weapon for each combination of aircraft, target, and weather state and computes a composite effectiveness for an aircraft sortie against a target using an input weather distribution. HEAVY ATTACK also does not model aircraft attrition; available sorties are an input, and the model's allocation does not affect available sorties. HEAVY ATTACK does not contain budget constraints, and only has the single objective of maximizing TVD. The amount of aggregation in the model, along with the use of advanced nonlinear programming techniques, makes HEAVY ATTACK very small and very fast, with response times in seconds.

The Theater Attack Model (TAM) was developed by the Air Force Studies and Analyses Agency in the mid-1980's, and at one point was given serious consideration

*APPLICATION AREAS:*
Air Warfare COEAs, Weapon System Acquisition

*OR METHODOLOGY:*
Wargaming

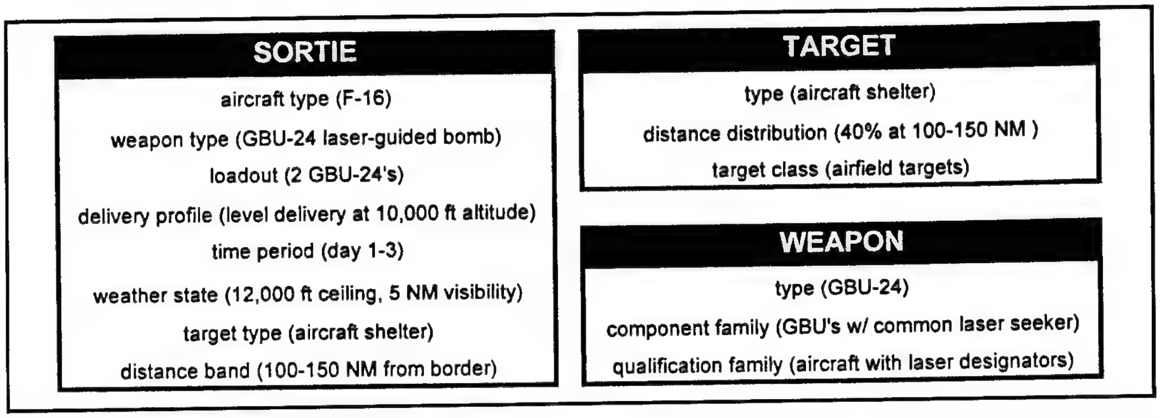


**Figure 1.** Dimensions of the primary entities in existing munitions models. The models all use sorties, weapons, and targets, but with different levels of detail. This figure gives an example of each dimension.

as a replacement for HEAVY ATTACK (Might [1987], Jackson [1989]). TAM is highly detailed, allocating sorties by aircraft, weapon, target type, target distance, weather state, and time period. In addition, TAM offers multiple objective functions, budget constraints and attrition constraints. The most common TAM objective is maximizing TVD; as opposed to HEAVY ATTACK, all TAM's objective functions are linear. BDA is not modeled in TAM, but available sorties are affected by attrition. TAM weather differs from HEAVY ATTACK in that TAM assumes the weather is known perfectly. However, the model uses the weather distribution to constrain the proportion of the time each sortie type can be used. TAM optimizes globally across time, but this feature and other dimensions in the model make the resulting optimizations very large. TAM solution times for typical scenarios and current hardware take about an hour.

MIXMASTER is a collective name for an optimization model and an heuristic developed at the Air Force's HQ Air Combat Command in 1990. The MIXMASTER linear program (LP) is a time-myopic version of TAM with only the TVD objective function, while the MIXMASTER heuristic is a greedy sortie allocation scheme that uses target values to determine the proportion of sorties dedicated to each target type. MIXMASTER was built as a response to dissatisfaction with HEAVY ATTACK, and the developers were directed *not* to use optimization. The LP version of MIXMASTER was written only as a check for the heuristic (Langbehn and Lindsey [1991]). The MIXMASTER heuristic is very fast, determining a solution in a few seconds; the LP, being a subset of TAM, runs in minutes.

The Conventional Targeting Effectiveness Model (CTEM) was developed for HQ USAF/XOOC (also known as Checkmate) in 1990 for analysis of current operations (Cotsworth [1993]). CTEM is a conventional derivative of the widely-used Arsenal Exchange Model (AEM), which has long been the standard for force structure analyses for nuclear weapons. CTEM is more of an optimization system than a specific model, as the user can shape the objectives and constraints in many ways. Typically, CTEM is used as a preemptive goal program where targets are grouped into target classes that must be attacked in a certain priority order; CTEM users normally do not use target values. In addition, CTEM has the capability to allocate suppression of enemy air defense (SEAD), and jamming sorties. CTEM does have some BDA modeling capability, can assign multiple costs to aircraft and weapons, and either constrain or optimize any combination of these costs. CTEM solution times range from one to three hours, depending on the scenario being analyzed.

## MODEL CONSOLIDATION

The differences among these four models led to serious disagreements over weapons requirements, which became harder to reconcile as the Air Force's procurement budgets began shrinking in 1990. At the same time, the Air Force began to take a more active role in controlling model development and proliferation, and became interested in reducing the number

| | HEAVY ATTACK | TAM | MIXMASTER | CTEM |
|---|---|---|---|---|
| **Objective function** | | | | |
| linear-target value | | X | X | X |
| nonlinear-target value | X | | | |
| goal | | | | X |
| multiple | | X | | X |
| **Sortie dimensions** | | | | |
| aircraft | X | X | X | X |
| weapon | | X | X | X |
| target | X | X | X | X |
| loadout | | X | X | X |
| time period | | X | | |
| distance band | | X | X | X |
| weather state | | X | X | X |
| user-defined | | | | X |
| **Target dimensions** | | | | |
| type | X | X | X | X |
| distance band | | X | X | X |
| user-defined | | | | X |
| **Time approach** | | | | |
| myopic | X | | X | X |
| global | | X | | |
| **Miscellaneous** | | | | |
| BDA | X | | | X |
| weather known | | X | X | X |
| weather unknown | X | | | |
| budget | | X | | X |
| SEAD/jamming | | | | X |
| attrition affects sorties | | X | X | X |

**Figure 2.** Capabilities of existing munitions models. The existing models vary widely with respect to objectives, constraints, and dimensionality.

of models addressing similar problems. After a study was completed comparing the various models (Yost [1995]), three of the owning USAF agencies agreed to consolidate their optimizations into one system, since their missions concentrated on munitions tradeoffs and requirements. As a result HEAVY ATTACK, TAM and MIXMASTER were destined to be replaced by a single system. The agencies felt a consolidation would be advantageous for all; a new development would advance the capabilities of this class of models, leverage their investment in common databases and data management tools, and provide a common framework for their analyses.

CTEM, on the other hand, was built to handle the allocation problem, and it did not contain some of the capabilities necessary for requirements and tradeoff analyses. Also, Checkmate was in the middle of imbedding it in much larger operational system, and it would have been disruptive to try to include CTEM in two large-scale efforts that had considerably different aims. Therefore, the Air Force felt it would be better to let CTEM continue as a separate model. However, CTEM has had an influence on the consolidated model, and the groups regularly share information on new and proposed methodologies.

The Air Force formed a working group to manage the consolidation, and this group gave the USAF Office of Aerospace Studies (OAS) the task of combining and extending the three models. Consequently, OAS produced two variants of the same formulations. The first set of models, collectively called QUICK STRIKE, operate as a sequence of optimizations. QUICK STRIKE optimizes sortie allocations for a single period, and passes the output from that period to the next period's optimization. This time-

myopic approach keeps the model small and fast, but complicates global analyses and forces the user, rather than the model, to explicitly define how resources can be used across time. The other variants, collectively called TIME STRIKE, globally optimize allocations across time. These two names survive as submodels under the new name for the entire system, which is the Combat Forces Assessment Model (CFAM).

Due to the complexity of CFAM and the number of inputs, this article contains only an abbreviated mathematical formulation. However, the entire formulation is available in Yost [1996], which also covers derivations of the submodels.

## CFAM: OBJECTIVE FUNCTIONS AND TARGET CLASSES

While CFAM is intended to be a consolidation, several features have been added that were not available in the existing models. Also, CFAM is not a single formulation; it offers user-selectable objective functions and constraints to allow the analyst to tailor the model to the issue at hand.

The CFAM models contain five different objective functions, three of which are retained from the existing models to give the users a sense of backward compatibility. Maximizing TVD, the most commonly-used objective in the existing models, is included in CFAM; in addition, CFAM includes two TAM objectives that don't use target values. The first minimizes aircraft attrition subject to a set of target destruction goals, while the second objective minimizes the cost of buying new aircraft and weapons subject to target destruction goals.

However, the user community was dissatisfied with the existing objective functions. The TVD objectives, while widely used, are difficult to control. In this class of models, the user typically has to tell the model what sort of campaign he wants to conduct, which generally means specifying sets of targets that have to be killed in a particular sequence, while constraining or minimizing attrition and resource expenditures. Attempts to use various methods such as the analytic hierarchy process to compute target values based on the user's view of the campaign rarely worked well because the optimization, which is juggling different resource availabilities and usage rates, often picks solutions apparently at odds with the user's values (i.e., the model killed 1000 bridges of value 1 and skipped the 10 command-and-control bunkers with value 100, but got the same TVD). The manipulation of target values was criticized by Lord [1982], and was a source of discomfort throughout the history of these models. For example, in the Air Force's annual requirements computations using HEAVY ATTACK, at least half of the analysis time was spent changing target values to induce the model to kill targets in the correct order. Users asked the reasonable question, why can't we just put in our campaign priorities? Why do we have to translate our aims into target values, and then change them constantly to get the model to do things in order?

It seems the TAM objectives to minimize either attrition or costs subject to a set of goals would be the answer. The problem with these objectives is that they are *inelastic*; that is, if the model can't kill all the targets required, it terminates as infeasible and yields little useful information. Also, the TAM objectives required the user to specify goal achievement at a particular time; the objectives could not minimize the time required to achieve a goal, which is a frequently-asked question. The working group wanted a cure for the inflexibility and a way to do the time minimization.

To overcome these problems, CFAM offers two elastic objectives. The first, called the *time-scripted* objective, allows the user to designate goals for destroying targets across time. CFAM minimizes the sum of the penalties associated with not achieving the goals, which keeps the model feasible if the goals can't be met. The time-scripted objective works well in cases where the user is evaluating a specified schedule for a campaign. However, users often want to determine the time necessary to achieve campaign objectives, so CFAM's remaining objective function is called the *phase-goal* objective. In this objective, the user divides the campaign into *phases*, which are sets of goals for each target class. The objective pursues the phases in a hierarchical order defined by the user, and attempts to minimize the time required to accomplish the phases. This objective allows the user to define overlap between the phases, so a phase can start before all the goals in the previous phase are met. As a result, the user can control each goal's degree of preemption (Figure 3).

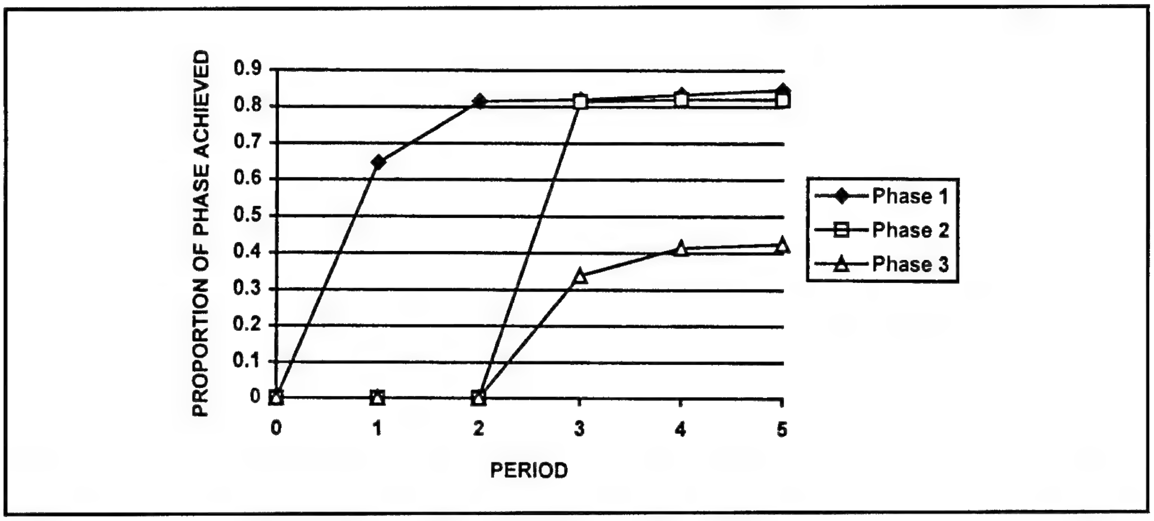


**Figure 3.** Phase-goal objective with thresholds. This campaign consists of 3 phases, with a .8 threshold for phase changes. Phases 2 and 3 can't start until Phase 1 is 80% complete, and Phase 3 can't start until Phase 2 is 80% complete. The threshold parameters allow the user to control the degree of preemption in the campaign phases.

CFAM's notion of target classes is a major difference from HEAVY ATTACK, TAM, and MIXMASTER, and supports the fact that campaign objectives involve killing collections of related targets rather than individual target types. CFAM allows a user to group a set of target types into a target class, set a time- or phase-dependent goal for their destruction, and rely on the model to treat them as a group.

In the example shown in Figure 4, the sector ops center is a member of both the airfield and integrated air defense system target classes. CFAM's phase goal objective function would require the user to define the proportion

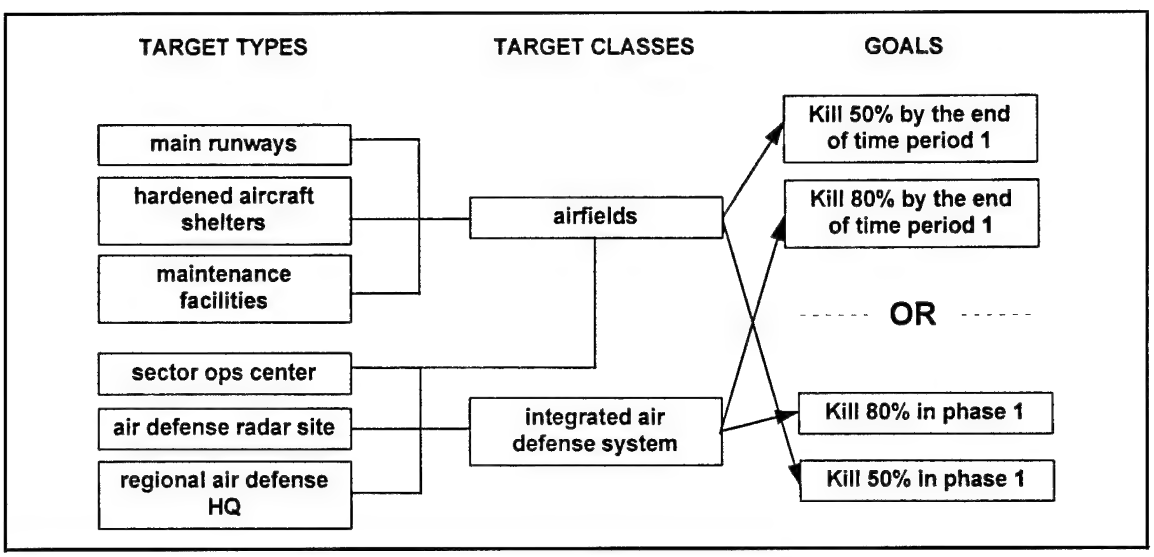


**Figure 4.** Targets, target classes, and goals in CFAM. A target can be included in multiple classes, and each class can have its own time- or- phase-dependent goal. User-defined penalties determine the importance of achieving each goal.

of targets in each class that need to be killed to complete the phase, while the other objectives would require the user to set proportions by time period.

In practice, the time-scripted and phase-goal constraints have largely replaced the use of target values. Users have found that the top-down specification of phases, goals, and target classes is much more natural than the bottom-up approach of using individual target values. If, for example, a CFAM user wants to first kill air defenses, and then concentrate on command-and-control targets, he can group those target types into classes, set requirements for how much of the target class must be killed in each time period or phase, specify the overlap he will allow in the phases, and run the model. If the model can't achieve the goals, then the elastic objective still tells the user which targets or target classes are causing problems, which is of considerable interest. In addition, the phase-goal approach explicitly minimizes the time to complete a phase.

Experience with CTEM (and 30 years of experience with its ancestor, AEM) has shown that a goal-orientation is much easier for users than a target-value orientation. Indeed, this is the most valuable insight that CTEM (and AEM) have contributed to CFAM's development; both CTEM and AEM allow target-value optimization, but users have always rejected it, citing its unpredictability. CFAM does not even allow the user to set the magnitudes of the weights or penalties; he can only choose the sign (reward or penalty) and the order (1 through n). The objective functions use built-in constants based on the priority of the phase and the priority of the target class within the phase, and leave the user to specify what he wants done when (in the time-scripted case), or in what order (in the phase-goal case). These constants are model performance parameters rather than external values, and are generally set to force a reasonable degree of preemption without causing scaling problems in the model. Our approach is not unusual; for example, Steuer [1978] reports similar problems with a forest-management model, and in that model the analysts also chose an ordinal (priority), rather than a weighted (value) scheme.

Again, the philosophy is to get the user to specify the desired campaign in natural terms (phases, time goals, target classes). Nonetheless, some analysts like target values, and CFAM can accommodate them as well.

## SORTIE AND KILL ACCOUNTING

CFAM unifies several ideas in the existing models about what can happen on each sortie and how kills are counted. Figure 5 shows all possible sortie outcomes in CFAM. The outcomes are straightforward. A sortie may not be scheduled due to an unfavorable weather forecast, an attrition limit which prohibits further flying, or an aircraft running out of a resource such as weapons. Also, the sortie is subject to a probability of an in-flight weather abort due to errors in the forecast. Expected kills and expected attrition for sorties that strike the target are inputs, and CFAM assumes the expected

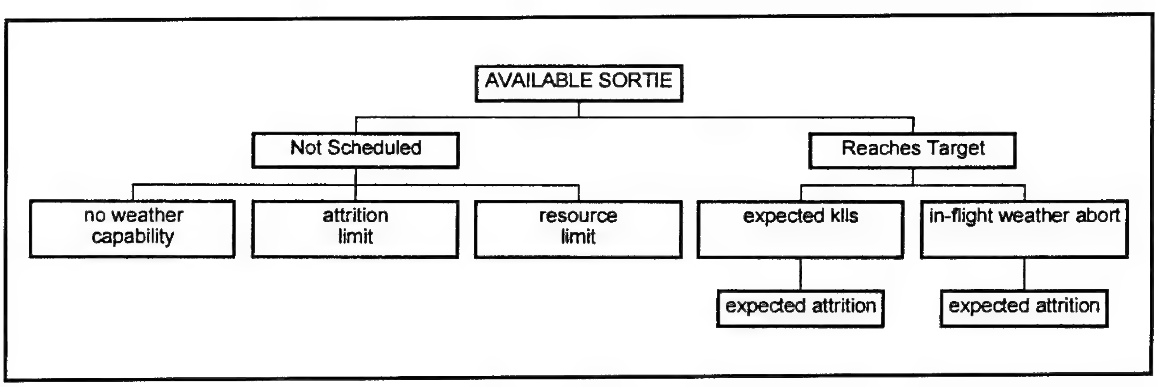


**Figure 5.** Possible outcomes of a sortie in CFAM. The available sortie may not be scheduled due to a lack of weather capability, the model already having lost too many aircraft, or the lack of a resource such as weapons. Otherwise, the aircraft reaches the target and is subject to attrition. The model computes expected kills for the cases that do not abort at the target due to weather.

kills are adjusted for the number of aircraft that are killed prior to reaching the target.

Once a target is struck, there are also several possible outcomes, as shown in Figure 6. This kill-accounting scheme captures an important effect—previously modeled only in HEAVY ATTACK—which is that a target can be killed, but misclassified and restruck. This dilution of sorties due to incorrect battle-damage assessment (BDA) is an important effect and must be represented in a realistic model. Another important effect is the ability of the enemy to regenerate (repair) dead targets. In both cases, CFAM has modified and extended the existing approaches, as discussed later.

## TIME MODELING

Time periods are necessary to model arrivals of aircraft and weapons in the theater, changes in sortie rates, shifts in campaign objectives, and changes in attrition rates. However, the existing models view time differently. Both HEAVY ATTACK and MIXMASTER are time-myopic, with output from each period's solution (with perhaps some external alteration) used as input for the next period. TAM, on the other hand, has an intrinsic time index in the formulation.

There are disadvantages to adding time to a model. HEAVY ATTACK can use a nonlinear BDA function and still remain small and fast because it only optimizes in a single period; adding time would enormously complicate the model. Explicit time periods also increase the size of the model. HEAVY ATTACK and MIXMASTER are small and quick because each period's optimization consists of 1,000–2,000 variables and a few hundred constraints. On the other hand, TAM can grow as large as 180,000 variables and 5,000 constraints, largely due to the intrinsic time index. As a result, TAM is usually run with only 4 periods of 3,7, 20, and 30 days, because the LP becomes too big to solve otherwise. Conversely, HEAVY ATTACK can run 20–30 myopic time periods in very little time.

In addition, there is a good argument for forcing myopia. The existing models conduct one-sided campaigns—the enemy has no choices. Letting an optimization look across time contradicts reality, particularly when the models assume the enemy doesn't react. This omniscience has been a perennial problem in TAM, which tends to wait for periods with low attrition rates to kill difficult targets unless explicitly constrained from doing so. TAM also uses its knowledge of the future to kill easy targets with high target values early so more of them are repaired and then restruck (earning more TVD).

Nonetheless, the myopic approach is a disadvantage for the analyst trying to solve a resource allocation or budgeting problem. If there is a fixed pool of procurement money available for a multi-period scenario, the analyst has to explicitly allocate or constrain expenditures by period. Since optimization is good at making these decisions, it seems unreasonable to force the analyst to guess the best time-constrained allocations outside of the model.

The compromise reached in CFAM is to use time explicitly in the model, but to limit the optimization's false omniscience. In CFAM, time is still divided into periods of user-selectable lengths, but now each period consists of an

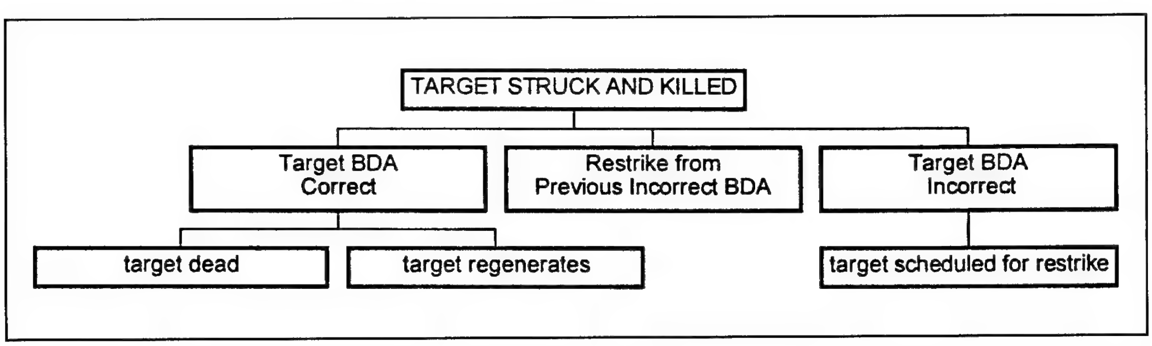


**Figure 6.** Possible outcomes of a target kill in CFAM. A kill may either have correct BDA, in which case it is either dead forever or regenerates, or it may have incorrect BDA and is scheduled for a restrike. Only one of the outcomes results in a permanent kill.

integral number of fixed-length *planning cycles*. A planning cycle is the number of days over which the campaign executes with no feedback; in other words, this is the assessment time lag. The planning cycle is key to CFAM's BDA and target regeneration submodels, because it reintroduces myopia and some of the so-called friction of war into the model. If it were possible to solve enormous models at no cost, CFAM would simply define the time period length as the planning cycle length. Unfortunately, this isn't possible, so the design team used the notion of a planning cycle to capture BDA and target regeneration effects within a period.

The analyst must weigh time fidelity in the model versus responsiveness when using CFAM. If the analyst needs many time periods for goal changes and aircraft arrivals, he can do so at the cost of generating a much bigger model. If his goals are coarser over time and he needs quicker turnaround, he can use fewer time periods and generate a smaller, faster model. In either case, the addition of the planning cycle cures problems with BDA and target regeneration within a period, as we'll discuss in the next section.

## BATTLE-DAMAGE ASSESSMENT AND TARGET REGENERATION

BDA has been a problem for the existing models, with HEAVY ATTACK being the only model that accounts for restriking dead targets due to bad BDA. In HEAVY ATTACK, the probability of restriking a dead target is a function of the number of targets already killed and a parameter known as the "C-factor," which varies between 0 and 1. A C-factor of 0 implies perfect BDA, while a C-factor of 1 implies no BDA and random targeting. There are two problems with this approach. First, the C-factor has no physical meaning. C-factors are not probabilities, but are merely adjustment factors that determine the marginal returns of continually attacking a particular set of targets (Lord [1982], Boger and Washburn [1985]). As a result, the analyst has to set the C-factors based on their effects on the model output rather than by using any available data.

Second, HEAVY ATTACK presumes that success in killing additional targets of a particular type is a function of the number of those types of targets already killed. For a collection of tanks on a battlefield in a short time interval, HEAVY ATTACK's BDA scheme is a good model. The more tanks that are killed, the more difficult it is for an attacker to discriminate among live and dead tanks. On the other hand, this is not a good model for fixed targets such as bridges. For these targets, the probability of a bad assessment has nothing to do with the number of similar facilities that have been bombed.

The BDA problem is an open research issue. In the meantime, CFAM's current BDA model is a compromise that keeps the model linear, explicitly defines the BDA factors, and denies the optimization's tendency to defeat BDA effects through omniscience. First, CFAM uses a single BDA input for each target type, which is a static probability of misclassifying a dead target as still being alive. Second, CFAM does not allow credit for any more kills against that target type until each misclassified target is restruck, as shown in Figure 7. In this example, T1 contains 2 planning cycles. CFAM assumes kills occur uniformly across a time period, so half of the misclassified targets happen in the first planning cycle of T1 and must be restruck in T1, while the other half must be restruck in T2. On the other hand, T2 contains 4 planning cycles, so 3/4 of the targets struck in the period that have incorrect BDA must be restruck within T2.

This mechanism allows us to capture the BDA effects *and* the lag effects in long time periods. If the model could wait until the next period to restrike targets, it would tend to wait until the *last* period to accumulate kills and avoid the workload caused by bad BDA. This can't happen in CFAM, as kills against these targets are discounted and the model prohibits additional kills against other targets until the bad BDA workload is accomplished. Conversely, the planning cycle lag forces some semblance of reality by making the model wait to recognize the need to do restrikes.

Target regeneration also uses the planning cycle. CFAM lags the detection of regenerated targets by one planning cycle, using the same logic as it uses for incorrect BDA. Again, the assumption of the planning cycle is that the sortie allocation is fixed over the length of the cycle, and the model cannot act on new information until the next cycle. Therefore, a newly-regenerated target must wait one cycle before it can be retargeted.

A serious limitation of the existing models is that they do not allow target regeneration

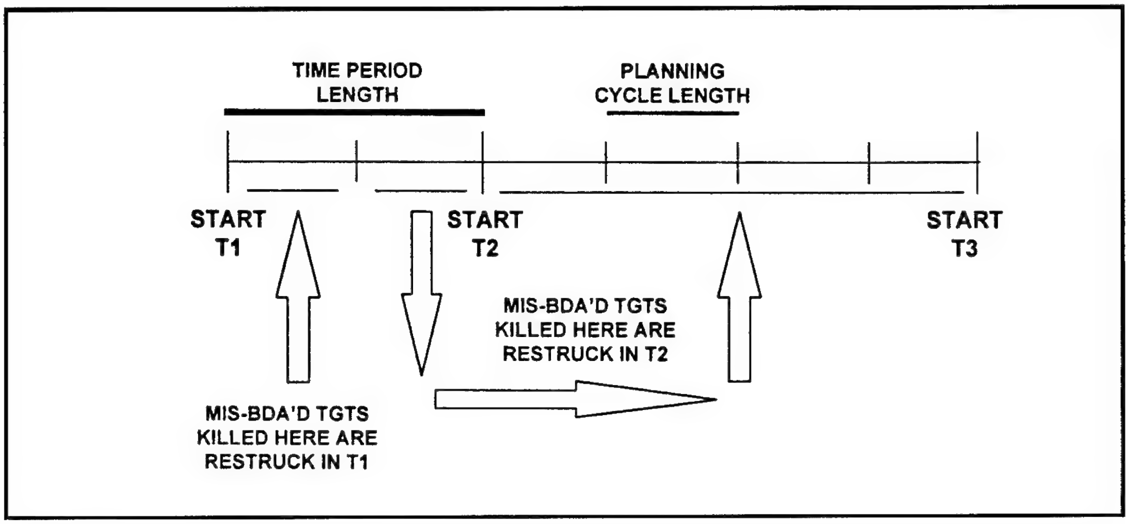


**Figure 7.** Time periods, planning cycles, and BDA in CFAM. Period T1 contains 2 planning cycles. Incorrect BDA from targets struck in the first planning cycle of T1 forces restrikes in the second planning cycle of T1, while incorrect BDA in the second planning cycle of T1 forces restrikes in period T2. This approach allows for both a lag time to recognize bad BDA and the ability to schedule restrikes within a time period.

within a period, which is a problem for targets with short repair times in long time periods; in addition, they do not allow control of the number of targets regenerated. CFAM allows multiple regenerations and retargeting within a time period, up to the number of planning cycles. Since the objective functions only count the target's status at the end of a time period, CFAM must allocate additional sorties to keep a target dead or in repair. CFAM can also control the total number of targets regenerated by using an input repair proportion to determine the expected number of targets repaired after every planning cycle. The user can also adjust this parameter to implicitly constrain total repair capacity.

Target regeneration and BDA are implemented in one submodel, which is derived in Yost [1996].

## WEATHER EFFECTS

The existing models describe weather in terms of "weather states", which are mutually exhaustive combinations of ceiling and visibility. Historically, the munitions-analysis community has partitioned the distribution of weather into 6 states and has used the proportion of the time the weather is in each state as a static input. These states affect the model because each aircraft-weapon combination has a number of *delivery profiles* associated with it, and each profile is valid only in certain weather states. For example, a medium-altitude profile might only be possible in the best three weather states, while a low-altitude profile using radar bombing might be possible in any weather state.

TAM and MIXMASTER assume perfect weather knowledge. There is no sense of a forecast, and these models assume the weather states occur in their fixed proportions in each period. On the other hand, HEAVY ATTACK models weather through its weapon-aggregation scheme. This procedure is equivalent to assuming that the weather is unknown when aircraft are allocated to targets, but known when weapons and delivery profiles are selected.

Unfortunately, neither assumption is true. Campaign planners don't have perfect weather knowledge, but they can forecast with some degree of accuracy. This issue has become more important as we develop autonomous (and expensive) weapons that have guidance systems unaffected by weather, because we need to correctly measure the payoff from having such weather-resistant weapons. CFAM does not offer a complete solution to the weather problem, but takes a step further than existing models by

forcing sorties to be scheduled in accordance with the distribution of *forecast* weather rather than the distribution of *observed* weather. More importantly, CFAM dilutes scheduled sorties by using the probability of forecast error to determine the number of in-flight weather aborts.

As an example, consider the following data provided by the Air Force Environmental Technical Applications Center in Figure 8.

A delivery profile that is valid in any particular weather state (WX) is valid in any higher state. Therefore, CFAM selects delivery profiles based on the forecast using cumulative constraints. In this example, 2% of the targets are forecast to have weather WX 1, so 2% of the scheduled profiles must be capable in WX 1. Since the 5% of the targets forecast for weather in WX 2 could also be hit with WX 1-capable profiles, 7% of the scheduled deliveries must be capable in WX 1 *or* WX 2. The CFAM weather constraints work in this cumulative fashion for all weather states. Note that if an aircraft type is only capable in WX 6, then CFAM would assume 19.4% of the available sorties for that aircraft type are lost in the period; these sorties are unscheduled and are not subject to attrition.

To account for forecast error, CFAM uses the conditional probability the weather is invalid for the profile, given a forecast of valid weather for the profile. This probability determines the proportion of sorties that aren't aborted in-flight due to weather; data for this example is shown in Figure 9. Suppose the model uses a profile whose minimum weather state is WX 3. Given the forecast was for WX 3 or better, there is a .8596 probability the weather will be WX 3 or better. When the model schedules WX 3 deliveries based on a forecast, 85.96% of them reach the target and 14.04% abort. An important assumption is that an aircraft that suffers a weather abort is still subject to attrition; in other words, the aircraft goes all the way to the target before discovering it can't deliver the weapons.

The CFAM weather model is conservative in that, in reality, aircraft can often be rerouted in flight to a secondary target based on weather information provided by earlier attacks. While we could model this as some sort of proportion, we have elected to keep the model conservative since there is so many other "fog of war" issues that we do not handle. Also, CFAM does not degrade attrition rates in bad weather, which would be the case for optical- and infared-guided air defenses which can't see the attacker. The latter problem may be addressed in a future upgrade, which will expand the attrition submodel; for now, we have again chosen to be conservative.

## INPUT FILTERS AND OPERATIONAL LIMITS

CFAM uses a number of factors outside of the formulation to limit the number of alternate sortie types. This is necessary because the number of possible combinations is very large. A typical scenario may contain 9 aircraft types, 90 target types, 300 delivery profiles, and 60 weapon types; in addition, aircraft may carry smaller loadouts of the same weapon to extend their range. When combined with multiple time periods, these combinations can easily lead to an LP containing several hundred thousand variables.

| WEATHER STATE (WX) | PROBABILITY OF FORECAST |
|---|---|
| WX 1 | 0.020 |
| WX 2 | 0.050 |
| WX 3 | 0.040 |
| WX 4 | 0.031 |
| WX 5 | 0.053 |
| WX 6 | 0.806 |
| TOTAL | 1.000 |

**Figure 8.** Marginal forecast probabilities by weather state. Higher numbers indicate more favorable weather. For example, WX 1 represents a ceiling of 0 feet and 0 NM visibility, while WX 6 represents a ceiling of 12000 feet and a 5 NM visibility.

| WX REQUIRED FOR PROFILE | PROPORTION NOT ABORTED |
|---|---|
| WX 1 OR BETTER | 1.0000 |
| WX 2 OR BETTER | 0.9502 |
| WX 3 OR BETTER | 0.8596 |
| WX 4 OR BETTER | 0.8185 |
| WX 5 OR BETTER | 0.7675 |
| WX 6 | 0.7665 |

**Figure 9.** Non-abort proportions by weather state. These are the proportion of the time the weather is in a particular state or better, given the forecast was for a particular state or better.

The first step in CFAM preprocessing is to remove *dominated profiles* from the database. These are delivery profiles for a particular aircraft-weapon-target combination that have a lower effectiveness and a higher attrition than another available profile that can be used in that weather state. This simple screen removes up to 30% of the possible aircraft-weapon-profile combinations. The second step involves removing operationally infeasible combinations of aircraft, weapons, and targets from the database. This is done externally, and the amount of reduction depends on how many cases the user is willing to rule out.

Next, the preprocessor filters the inputs based on two user-supplied settings: the minimum expected kills per sortie (EKS); and the maximum attrition per sortie. Attrition and EKS limits are present in various forms in the existing models' preprocessors, but their use is emphasized in CFAM. An aircraft-weapon-delivery profile combination that has a probability of .001 of killing a target and a probability of attrition of .25 is unlikely to be chosen in the optimization, and would *never* be chosen in reality. Therefore, users should be aggressive with these filters and throw out as many excess variables as possible prior to running the LP. Computational experience with TAM shows that LP's in this class only choose a few hundred deliveries out of several hundred thousand, so it makes sense to remove the inefficient alternatives before presenting them to the model.

The final screen is based on an operational constraint that is not treated in the existing models: the minimum operating altitude in the period, commonly known as the *hard deck*. Hard decks are real and crucial operating constraints in modern air warfare. If the theater commander decides to fight a medium-altitude war such as DESERT STORM, a great number of delivery tactics are simply not available. In addition, weapons effectiveness, particularly for visual deliveries, varies greatly with release altitude.

Figure 10 shows a typical reduction due to applying these filters. Reductions of an order of magnitude in the number of sortie cases are not uncommon.

## TWO-THEATER MODELING

Currently, the US national military strategy requires support of two near-simultaneous

| | NUMBER OF CASES |
|---|---|
| **INITIAL DATABASE** | 37,000 |
| after excluding DOMINATED PROFILES | 26,000 |
| after excluding OPERATIONALLY INFEASIBLE CASES | 10,000 |
| after applying FILTERS (effectiveness, attrition, hard decks) | 3,000 |

**Figure 10.** Input filtering for CFAM. Applying filters for dominated profiles, operational infeasibility, effectiveness, attrition, and hard deck settings can remove over 90% of the possible sortie combinations prior to running the model. Using the filters can drastically reduce the size of the LP.

"major regional conflicts" (MRC's). Unfortunately, none of the existing models allow for two theaters. As a result, CFAM allows for two-theater campaigns, so the analyst can develop requirements for both theaters simultaneously. The first campaign starts in the first time period, and the second campaign can start in any time period. The analyst can divide the budgets among the theaters or use additional constraints to bound the overall resource consumption in both theaters.

Another important capability in CFAM is the ability to *swing*, or redeploy, aircraft from the first campaign to the second. Force reductions have led the USAF to adopt a swing doctrine for certain high-value, high-leverage assets such as the F-117. However, the question of when to swing these aircraft and how many to swing is an open issue. CFAM can optimize the timing and number of swing aircraft, given user-supplied bounds on the number that can swing and when they can swing.

All the machinery available in one campaign in CFAM is implemented in the two-theater formulation. The theaters have separate target sets, separate weather distributions, BDA rates, regeneration rates, sortie rates, force structures, and so on. This capability does not come without cost; a two-theater LP can become very cumbersome, making intelligent use of the filters very important.

## BUDGET CONSTRAINTS

HEAVY ATTACK and MIXMASTER do not contain budget constraints. The most common version of TAM has one budget constraint, which is applied globally. Aircraft and weapons in TAM have marginal costs, and the model can either purchase assets subject to a spending constraint or minimize the amount spent to achieve certain goals. However, the TAM budget scheme has two shortcomings. First, the single budget isn't flexible enough to account for different types of resources consumed by weapons and aircraft, such as procurement funds, airlift, and airfield space. Second, it doesn't distinguish expenditures on aircraft, which are long-term assets, and munitions, which are expendables.

To address these problems, CFAM contains four different budgets in two categories, and the analyst can use any or all of them as constraints. The categories are called *carry* and *no-carry* to denote how the resource can be spent across time. A carry budget represents a resource such as procurement funds; it has no relation to time within the model, because the goal is to determine the investment necessary to meet campaign goals in a future conflict. Conversely, a no-carry budget represents a resource that must be used within a time period; unused resources don't "carry" to succeeding periods. This budget models resources such as airlift, which must be spent when available and can't be saved. There are two carry and two no-carry budgets available in CFAM.

One limitation of CFAM is that assets can only be bought in one budget; purchased assets do not consume a vector of resources, as shown in Figure 11. For example, buying a weapon cannot simultaneously consume procurement dollars and mobility resources; the assets are only available in each budget, and each budget must have its own upper bounds on aircraft and weapon purchases. This may seem to be an unreasonable assumption, but design team chose to implement budgets this way to avoid unnecessarily complicating the formulation to address a set of problems that have yet to come up in practice.

## AIRCRAFT ATTRITION

CFAM uses an approach similar to TAM's for modeling aircraft attrition. Each feasible combination of aircraft, weapon, target, and delivery profile suffers an input proportion of attrition based on the time period; however, targets killed by the model do not affect these attrition rates. Changes in attrition rates due to enemy air-to-air or surface-to-air assets as a function of time are determined externally to the model. CFAM uses these inputs to constrain or minimize attrition, depending on how the user is running the model.

However, the user has the option in CFAM to specify how attrition affects sortie generation. In TAM, attrition reduces the number of available sorties. CFAM offers this option (see the formulation), but also offers the option of turning off the sortie reduction. The first case is the same as assuming no replacement aircraft are available. In the second case, the user assumes all losses are replaced within the time period and the remaining aircraft can temporarily fly more sorties to account for the missing aircraft prior to its replacement; as a result, no

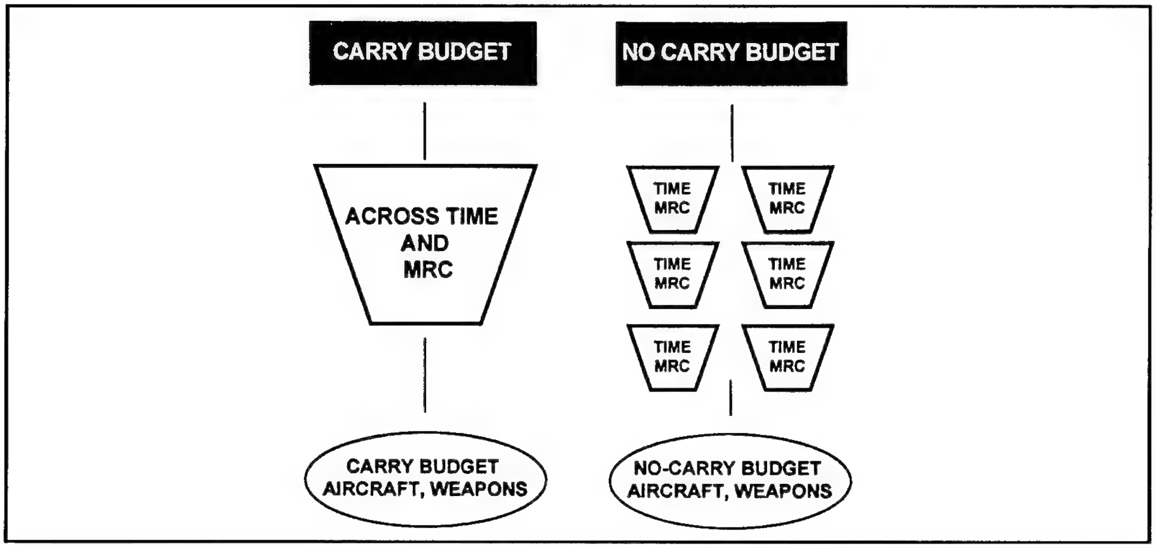


**Figure 11.** CFAM budgets. Each budget type has its own pool of aircraft and weapons. The carry budgets represent resources that can be spent across time and theater (MRC), while the no-carry budgets represent resources that can only be spent when and where they are available.

sorties are lost due to attrition. However, CFAM can still constrain aircraft losses in the second case.

## IMPLEMENTATION AND COMPUTATIONAL EXPERIENCE

The CFAM models are straightforward linear or mixed-integer programs that do not require special solution techniques. Therefore, the Air Force has chosen to use GAMS (Brooke, Kendrick, and Meeraus [1992]) to generate the models. The system can use any commercial LP solver that interfaces with GAMS, and input and output are managed by a graphical user interface written in Visual BASIC. While the interface is hosted on the PC, the actual model can be run on either a PC or a workstation-class system (Figure 12).

TIME STRIKE's performance depends on the size of the data set, the objective function used, and the amount of filtering. Current 1-MRC scenarios consider approximately 9 aircraft types, 60 weapons types, 70 target types distributed in 4 distance bands, 7 time periods, 6 weather states, 10 target classes, and 3 phase goals. These problems result in formulations containing approximately 20,000 variables and 7,000 constraints; however, subsequent filtering after one or two tuning runs reduces the LPs to roughly 7,000 variables and 2,000 constraints for time-scripted goals, and 8,000 variables and 3,000 constraints for phase goals. Experience has shown it is better to run TIME STRIKE a few times with a small number of time periods to identify clearly unproductive sortie combinations and test the feasibility of the campaign goals. Subsequent runs with filtering go considerably faster, and some of the solvers allow us to save previous solutions and do a "warm start" for runs with minor changes. Solution times on current PC's range from 2 to 11 minutes, depending on the choice of LP solver. GAMS overhead in generating the model is modest, ranging from 1 to 3 minutes. A separate column-generation utility is available for TIME STRIKE to allow the user to consider all combinations without filtering.

QUICK STRIKE is much less sensitive to problem size, because it solves as a sequence of optimizations. The scenario discussed above would generate an LP with approximately 2500 variables and 1000 constraints for each time period, and these problems will solve in less than one minute each. However, the user must allocate resource across time manually, so it is better to use TIME STRIKE and QUICK STRIKE together. TIME STRIKE can give advice to QUICK STRIKE on how to allocate resources such as budgets and attrition across time, while QUICK STRIKE can help determine how to set

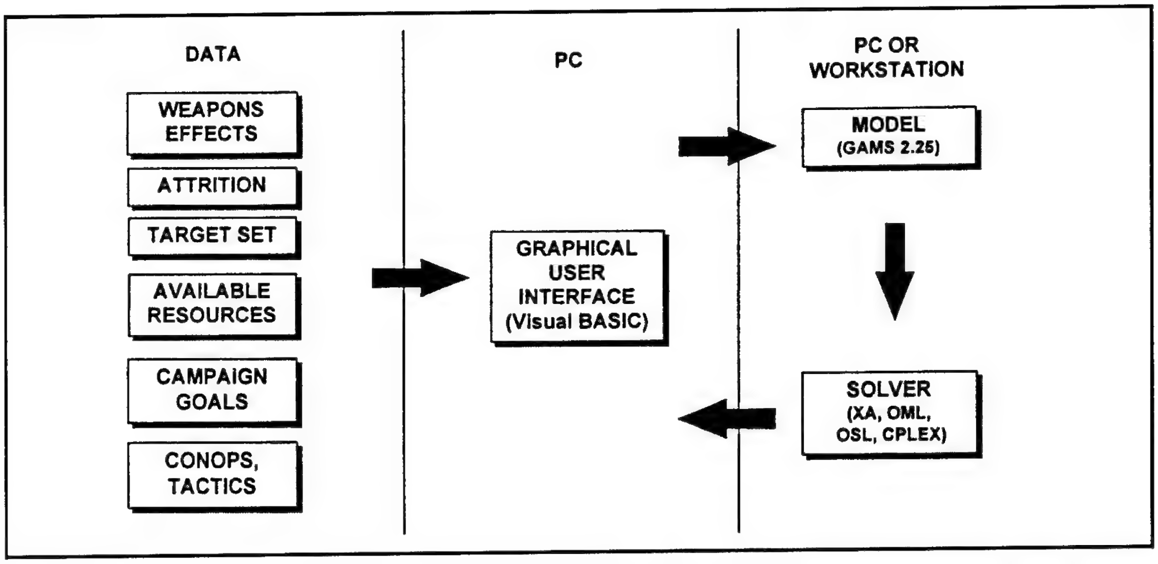


**Figure 12.** CFAM structure. This diagram shows the fundamental parts of the CFAM system, along with the commercial software used.

the time periods in TIME STRIKE. For example, a TIME STRIKE run with 4 12-day time periods may show that 60% of a budget should be spent in the first 12 days, while the rest should be saved for the last three periods. QUICK STRIKE can then be constrained to leave 40% of the budget for the last 36 days of the campaign; otherwise, due to its myopia, it may choose to spend its budget too soon and cripple capability in later periods. Conversely, QUICK STRIKE, running 3-day periods may show that phase changes occur only in days 4–6 and 19–21, enabling the user to reduce the number of time periods in TIME STRIKE to 3 (1–3, 4–18, and 19–48), cutting down on the size and run time of the model.

## GUI DEVELOPMENT AND DATA AVAILABILITY

The reader may have noted that a tremendous amount of data has to be supplied to CFAM, and nearly all of this data is tightly coupled. In the past, users relied on an ad-hoc combination of databases, spreadsheets, and utilities to manage and preprocess this data, and analysts frequently found themselves doing two weeks' worth of database preparation to support two days' worth of analysis. As a result, the Air Force has put a substantial investment into the development of a graphical user interface (GUI) to handle input, execution, and output. The GUI, written in Visual BASIC, will centrally manage all input and output, and for the first time the fundamental input data will be stored in databases rather than flat files of varying formats. While GUI development is not of primary interest to the readers of this journal, it is important to note the GUI should deliver nearly as much improvement in productivity as CFAM itself.

If CFAM had been built with no predecessors, it is doubtful the Air Force could have generated the data for this model. As it turns out, CFAM benefits from 25 years' of experience with HEAVY ATTACK, TAM, and MIX-MASTER, because entire data systems and management relationships already exist to support those models. For example, the attrition database is the full-time occupation of an entire group of analysts at Eglin AFB, and involves running a complicated suite of simulations to develop attrition information for each mix of aircraft, target, profile, and scenario. Weapons effects data is similarly complicated to generate, but CFAM can rely on the services' continued investment in the Joint Technical Coordinating Committee's Air-to-Surface group for development of standard methodology and software to build kill probabilities for various weapons. Conversely, the BDA methodology is deliberately simple because data currently does not exist to support a more complex submodel.

## FUTURE EFFORTS AND COMMENTS ON THE CONSOLIDATION

CFAM development continues. A submodel for the air-to-air part of the campaign is being tested, and research is in progress on a formulation that allows the model to allocate SEAD (suppression of enemy air defenses) assets. There is also a variation of the CFAM formulation that allocates sensors to targets, so the model must first find a target before attacking it and then allocate another sensor look to perform BDA. This will unify the detection and BDA submodels and allow us to directly assess the value of sensors. The final (and most ambitious) research effort is to use game-theoretic concepts to extend CFAM to a two-sided model.

However, the model as described here has been used for several munitions studies already, and it will replace HEAVY ATTACK in 1997 as the Air Force's standard for determining weapons requirements. CFAM is managed by the Air Force Studies and Analyses Agency, and a user's group that coordinates distribution, documentation, and modifications is in place.

This effort was easy in one sense because it was based on existing models, but considerably more difficult in another because it was a consolidation. Many of the users of the existing models had spent years mastering and improving their particular system, and they were reluctant to give up methods that were provably poor in theory but demonstrably effective in practice. Also, the entire group had to constantly battle the tendency to throw great numbers of marginally useful extensions into the system. A good example of this was our debate over budgets. Of the existing models, only TAM had a single budget, while the other two had no budget capabilities at all. In spite of this, several users felt the *four* budgets installed in CFAM were insufficient. Much of this desire for new capabilities was a result of pent-up demand, as none of the models had been significantly extended in many years.

Although the Air Force has succeeded in this case in eliminating a set of partially duplicative models, there is something to be said for having competing approaches available. The reader may have noted that none of the existing models was all good or all bad; each had its advantages and drawbacks. Many of us involved in the development of CFAM have wondered whether our consolidation may cut off some of the natural competition that had evolved among these models. However, the corporate viewpoint is that the common investment will overcome this monopolistic behavior; in the past, no one organization had the funding or manpower to make sweeping upgrades in their model, but they can collectively make continual improvements in CFAM.

Optimization is a valuable and appropriate tool for the munitions problem. Optimization can consider a large number of force mixes far faster than a simulation-oriented approach, and models such as CFAM can make a huge number allocation and budget decisions in a single run. This, along with the sensitivity analysis available in linear programming, has made these tools invaluable to the Air Force for the last 25 years. This should be true for the next 25 years as well.

## ACKNOWLEDGEMENTS

The models discussed in this article are the result of a collective effort. A particularly important member of the development team was 1Lt Jay DeYonke, the principal author of QUICK STRIKE; Jay was responsible for many of the new ideas now embodied in CFAM. Also deserving credit are the members of the USAF Munitions Model Working Group: LtCol Bob Sheldon, LtCol Paul Schroeder, LtCol Doug Lincoln, Maj J. Q. Watton, Maj Ray Hill, Maj Bob O'Neill, Maj Mike Buck, Mr. Rich Freet, Ms. Lynne Willis, Mr. Nick Reybrock, and Mr. Dennis Coulter. Col Tom Allen, Col Craig Ghelber, and Col Frank Griffin agreed to set their organizations' models aside and pursue the consolidation that led to CFAM. The original NPS technical report was edited by Dr. Jerry Brown, Dr. Al Washburn, and Dr. Rob Dell; their comments greatly improved both the model and the documentation. Finally, I would like to acknowledge the numerous developers and users of HEAVY ATTACK, TAM, MIX-MASTER, and AEM/CTEM for their contributions over the last two decades. CFAM borrows freely from the many good ideas used in its predecessors.

## FORMULATION: INDICIES

The following formulation is for a single period with the time-scripted objective in a sin-

gle theater. As a result, there is no time index or theater index as is present in the full CFAM model, nor is there a discussion of the other objective functions. The full formulation, including derivations, is available in Yost [1996].

These are the indices used by the model.

| | |
|---|---|
| i | aircraft |
| j | weapon |
| k | target |
| l | loadout |
| p | delivery profile |
| w | weather state |
| d | distance band |
| c | target class |
| f | weapon component family |
| q | weapons qualification family |
| b | budget |

We also use the following to denote valid n-tuples (correspondences) of the index arguments. For example, **cc(k,c)** denotes the set of all admissible target-target class combinations.

| | |
|---|---|
| cc(k,c) | target-target class correspondence |
| fc(j,f) | weapon-component family correspondence |
| qc(j,q) | weapon-qualification family correspondence |
| r(i,j,l,d) | aircraft-weapon-loadout-distance band correspondence |
| wc(i,j,p,w) | aircraft-weapon-profile-weather state correspondence |

## FORMULATION: DATA

| | |
|---|---|
| $ACCOSTS_{ib}$ | budget **b** resource consumed per aircraft **i** |
| $ACMAXBUY_{ib}$ | maximum number of aircraft **i** available for purchase in budget **b** |
| $ATTR_{ijkp}$ | expected losses per sortie for combination **i,j,k,p** |
| ATTRWGT | objective function weight for attrition |
| $BDAREG_{k}$ | expected number of targets **k** dead or in repair at the end of the time period; adjusts for BDA errors and target regeneration |
| $BDGLIMIT_{b}$ | resource limit for budget **b** |
| $BUYWGT_{b}$ | objective function weight for spending in budget **b** |
| $CUMARRIVE_{j}$ | number of weapon **j** scheduled to arrive this period |
| $EKS_{ijklp}$ | expected kills per sortie for aircraft **i**, weapon **j**, target **k**, loadout **l**, profile **p** |
| $FAMLIM_{f}$ | maximum number of common components available for weapon family **f** |
| $GOAL_{c}$ | proportion of targets in target class **c** to be killed to achieve the current goal |
| $HISTFORECAST_{w}$ | cumulative proportion of forecasts for weather states **1** through **w** |
| $INVENT_{j}$ | inventory of weapon **j** on-hand |
| $LOAD_{l}$ | number of weapons carried per sortie for loadout **l** |
| $MAXLOSS_{i}$ | maximum losses of aircraft **i** allowed |
| MUNWGT | objective function weight for munitions use |
| $NABORT_{ijp}$ | proportion of sorties by aircraft i flying profile **p** with weapon **j** not aborted inflight |
| NDAYS | number of days in the time period |
| $PPEN_{c}$ | objective function penalty for not meeting the time-scripted goal for target class **c** |
| $PROPORTION_{iq}$ | proportion of aircrews manning aircraft **i** qualified to drop weapons in qualification class **q** |
| SORTWGT | objective function weight for sorties |

| | |
|---|---|
| $SR_i$ | sorties per day for aircraft **i** |
| $TIMEAC_i$ | number of aircraft **i** scheduled to arrive |
| $TOTTGTS_{kd}$ | total number of type **k** targets in distance band **d** |
| $TOTTGT_k$ | total number of type **k** targets |
| $TSORT_{ijkp}$ | expected number of sorties per aircraft for combination **i, j, k, p** considering attrition |
| $WPNCOSTS_{jb}$ | resources consumed per weapon **j** bought in budget **b** |
| $WPNMAXBUY_{jb}$ | maximum number of weapon **j** available in budget **b** |

## FORMULATION: VARIABLES

All variables are given in lower case.

| | |
|---|---|
| z | time-scripted goal objective value |
| $x_{ijklp}$ | sorties assigned |
| $pdiff_{kc}$ | proportion of kills below goal **c** for target **k** |
| $wpnbt_{jb}$ | weapons of type **j** bought in budget **b** |
| $acbt_{ib}$ | aircraft of type **i** bought in budget **b** |
| $onhanduse_j$ | existing inventory of weapon **j** used |

## FORMULATION: OBJECTIVE FUNCTION

Our experience has shown these LPs often have multiple optimal solutions, so we use small weights on attrition, sorties, munitions expenditures, and weapons and aircraft purchases to break these ties. These penalty terms are defined below:

$$at = ATTRWGT * \sum_{ijklp} ATTR_{ijkp} * x_{ijklp}$$

$$so = SORTWGT * \sum_{ijklp} x_{ijklp}$$

$$mu = MUNWGT * \sum_{ijklp} LOAD_l * [ATTR_{ijkp} * (1 - NABORT_{ijp}) + NABORT_{ijp}] * x_{ijklp}$$

$$bu = \sum_b \left[ BUYWGT_b * \left( \sum_i ACCOSTS_{ib} * acbt_{ib} + \sum_j WPNCOSTS_{jb} * wpnbt_{jb} \right) \right]$$

Note that these weights can be positive or negative; for example, a user may want to give a negative weight to SORTWT to influence the model to fly as many sorties as possible.

The following is the objective function for time-scripted goals for a single period. This minimizes the weighted sum of the proportions of each goal not achieved plus the sum of the tie-breaking weights:

$$\min z = \sum_{(k,c) \in cc(k,c)} (PPEN_c * pdiff_{kc}) + at + so + mu + bu$$

## FORMULATION: SIMPLE BOUNDS AND CONSTRAINTS

All CFAM variables are nonnegative, and all have simple upper bounds:

$$x_{ijklp} \le SR_i * NDAYS * TIMEAC_i * \sum_b ACMAXBUY_{ib}$$

$$pdiff_{kc} \le 1.0$$

$$wpnbt_{jb} \le WPNMAXBUY_{jb}$$

$$acbt_{ib} \le ACMAXBUY_{ib}$$

$$onhanduse_j \le INVENT_j$$

The following are the explicit constraints available in the model that are used with this particular objective function. The swing aircraft constraints are omitted because this example formulation only applies to one theater.

### Goal constraints:

$$\frac{\sum_{ijlp} (BDAREG_k * EKS_{ijklp} * NABORT_{ijp} * x_{ijklp})}{GOAL_{ct} * TOTTGT_k} + pdiff_{kc} = 1.0$$

for all **(k, c) ∈ cc(k, c)**.

Note that a target appearing in multiple target classes will have multiple positive (**pdiff**$_{kc}$) differences. This is intentional, as a target affecting multiple goals should accumulate multiple penalties in the objective function. Killing targets beyond the goal is not allowed.

## Aircraft-sortie constraints:

$$\sum_{jklp} \frac{x_{ijklp}}{TSORT_{ijkp}} \leq TIMEAC_i + \sum_b acbt_{ib}$$

for all **i**

**TSORT** is a constant computed for each sortie combination that determines the expected number of sorties that could be flown against a target by an aircraft over a fixed number of days with a fixed attrition rate. CFAM allows the user to choose whether attrition affects sortie generation or not; in the latter case, the user assumes all losses are replaced within the time period, and the remaining aircraft can fly more sorties to account for the missing aircraft prior to its arrival.

## Aircraft attrition constraints:

$$\sum_{jklp} ATTR_{ijkp} * x_{ijklp} \leq MAXLOSS_i$$

## Weapons use and weapons family constraints:

$$\sum_{iklp} LOAD_l * [ATTR_{ijkp} * (1 - NABORT_{ijp})$$
$$+ NABORT_{ijp}] * x_{ijklp} \leq onhanduse_j$$
$$+ \sum_b wpnbt_{jb} + CUMARRIVE_j$$

for all j

$$\sum_{j \in fc(j,f)} onhanduse_j \leq FAMLIM_f$$

for all **f**

The first constraint counts the number of sorties that either drop bombs on a target or suffer attrition during an in-flight weather abort; in both cases, the weapons are consumed. The second constraint addresses weapons that share common components, which is an important issue in munitions allocation. **FAMILYLIM**$_f$ gives the total number of available components, but this limit only applies to on-hand inventory. CFAM assumes purchased or arriving weapons are complete rounds.

## Budget constraints:

$$\sum_i ACCOSTS_{ib} * acbt_{ib}$$
$$+ \sum_j WPNCOSTS_{jb} * wpnbt_{jb} \leq BDGLIMIT_b$$

for all **b**

Since this example formulation only contains one time period and theater, it is not possible to show the difference between carry and no-carry constraints. In the full CFAM models, the budget constraints have different forms for the different types.

## Kills by distance constraints:

$$\sum_{(i,j,l) \in r(i,j,l,d),p} (BDAREG_k * EKS_{ijklp}$$
$$* NABORT_{ijp} * x_{ijklp}) \leq \sum_{d' \leq d} TOTTGTS_{kd'}$$

for all **k, d**

These constraints limit aircraft-weapon-loadout combinations to targets in valid distance bands. They are cumulative to allow longer-range deliveries to kill close-in targets. As a result, the **x** variables do not need an explicit index for distance, eliminating a large number of variables.

## Weather constraints:

$$\sum_{(j,p) \in wc(i,j,p,w),kl} \geq HISTFORECAST_w * \sum_{jklp} x_{ijklp}$$

for all **i, w**

These constraints force the model to schedule sorties in proportion to the average weather

forecast. To maintain feasibility, CFAM requires a dummy target and a dummy weapon that each aircraft can employ in each weather state. Otherwise, CFAM would force sorties to be scheduled for aircraft with no valid sortie combinations in particular weather states, making the model infeasible.

## Weapons qualification constraints:

$$\sum_{(j \in qc(j,q)),klp} x_{ijklp} \leq PROPORTION_{iq} * \sum_{jklp} x_{ijklp}$$

for all (i,q) with $PROPORTION_{i,q} > 0$

These constraints model situations where only a certain proportion of an aircraft's aircrews are qualified to employ a weapon, or only a certain proportion of an aircraft type are equipped to drop a weapon.

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# Satisfying Advanced Degree Requirements For U.S. Air Force Officers

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## ABSTRACT

A mathematical model is developed and implemented to determine the minimum number of Air Force officers that must enter graduate educational programs each year in order to satisfy personnel requirements by academic specialty, degree level, and military rank. The model is formulated as a Markov decision process and solved using linear programming. Analytical results were employed in a major re-engineering of the resident graduate schools at the Air Force Institute of Technology.

APPLICATION AREA: manpower & personnel

OR METHODOLOGIES: Markov processes, linear programming

## INTRODUCTION

Recent contingencies involving United States military forces support the view that "technological superiority is a principal characteristic of our military advantage" [4]. The U.S. Air Force has long understood that wise investment in advanced technology will result in improved mission effectiveness and fewer casualties. A critical component of this investment is the formal academic education of officer personnel in appropriate technical disciplines. More than half of the 78,000 Air Force officers currently on active duty hold master or doctoral degrees [9], many in highly technical fields of study. Moreover, the current USAF personnel structure includes over 5,000 positions which require specific advanced degrees as basic duty qualifications. The efficient management of these positions, and the officers qualified to fill them, relies on a classification system built on four-character academic specialty codes. For example, there are 35 coded positions for officers having master of science degrees in electrical engineering with emphasis on electro-optics (specialty code 4IJY). These 4IJY positions may be located within Air Force laboratories, test organizations, or program offices which manage weapon system acquisition. To ensure appropriate experience levels, all positions are controlled not only by academic specialty code and degree level, but also by grade (military rank).

Air Force personnel can receive the advanced academic education needed to qualify for a position through one of several methods. A small number of individuals obtain appropriate advanced degrees prior to entering military service. Some officers earn pertinent degrees during their off-duty time at colleges and universities near their duty stations. However, these "external" sources fall far short of satisfying total requirements, particularly in specialized technical areas. Satisfaction of this demand is a primary mission of the Air Force Institute of Technology (AFIT) at Wright-Patterson Air Force Base, Ohio. Since the birth of its parent service in 1947, AFIT has been chartered to provide selected officers with advanced education having "specific objectives derived from the needs of the Air Force" [12]. Upon selection for an AFIT assignment, an officer becomes a full-time student in a funded degree program in exchange for a specified Active Duty Service Commitment. This contractual concept recognizes that the opportunity for a funded graduate education is a powerful recruitment and retention incentive for intelligent and productive people [8]. Through its Civilian Institutions program, AFIT maintains Educational Services Agreements with universities throughout the country. The Institute also operates two resident schools at the Wright-Patterson campus: the Graduate School of Engineering, and the Graduate School of Logistics and Acquisition Management. These accredited schools provide responsive, defense-focused graduate education which takes full advantage of the Institute's collocation with major Air Force laboratories and acquisition centers. Because of AFIT's unique charter, faculty and students can be thoroughly immersed in defense-oriented research and consultation projects.

In the aftermath of the Cold War, the Air Force has undergone significant organizational changes and has experienced drastically reduced force levels. These changes have been accompanied by reduced annual quotas for graduate education. Total Air Force officer manning levels will decrease by about 29% between 1989 and 1999, after which force levels are expected to stabilize. The personnel populations serviced by the AFIT resident schools have been projected to decrease by about 34% over the same period. By March 1995, it became clear that AFIT must adjust its programs and size to respond to a changing environment, but it was less clear what those adjustments should be. Massive organizational changes and shifting personnel requirements rendered historical quota data somewhat irrelevant to future planning. This situation led the AFIT Commandant to initiate a re-engineering study to review the AFIT mission, determine the size and scope of the graduate schools, and propose an implementation plan. A key

component of this study was the quantitative conversion of Air Force personnel requirements into annual flows of educational program entries. This article describes an analytical model which was developed for this purpose. The model reduces to a linear programming formulation of a Markov decision process, which can be specifically employed to determine the minimum number of officers that must enter MS or PhD programs each year in order to consistently satisfy all personnel requirements within an academic specialty.

The dynamic behavior of a personnel system can be effectively described by probabilistic transitions between distinct system states. Hence, Markov process modeling offers a natural analytical approach that appears frequently in the relevant literature. In 1973, G. S. Davies proposed a Markov chain model for use in controlling a general graded manpower system [3]. Concepts from this approach were subsequently applied in a general force structure model for Air Force career specialties [2]. Several years later, Markovian assumptions were employed in a specific analysis of advanced degree positions within the Air Force civil engineering career field [13]. This effort essentially produced a highly simplified version of a descriptive computer model developed earlier at the RAND Corporation. The principal attribute of the RAND model was its "capacity to create future expected values of personnel inventories given the starting distribution and a matrix of transition probabilities" [10]. The approach developed in this article employs a Markov decision model [5, 6, 7] to not only describe process behavior, but also determine the educational policies that will satisfy validated personnel requirements (by degree level, grade, and academic specialty) at minimum cost. Since the ultimate objective of the analytical effort is to prescribe organizational sizes and structures for the AFIT graduate schools, a long-run perspective is necessary. While annual educational quotas may fluctuate from year to year based on current inventories and other factors, a "steady-state" model can provide valuable insights which prevent transient phenomena from inappropriately dominating structural decisions.

## MODEL FORMULATION

The first step in formulating the model is the identification of a discrete state space (that is, a set of the possible states which characterize an individual officer at a point in time). For this analysis, a state is sufficiently defined by the vector $(i, k)$, where $i$ is longevity (years of service) and $k$ is the cumulative number of years of graduate education. Two years of graduate education correspond to a MS degree, and five years correspond to a PhD degree. At one-year intervals, an officer may transition between states as shown in Figure 1. Some of the transitions are probabilistic. For example, an officer in state $(i, k)$ may leave the Air Force with some probability, in which case he is globally replaced by a new officer with no longevity (moves to state (0, 0)). Any officer who completes 24 years of service is assumed to either retire or depart the qualified inventory pool for a senior "executive" position. In addition, an

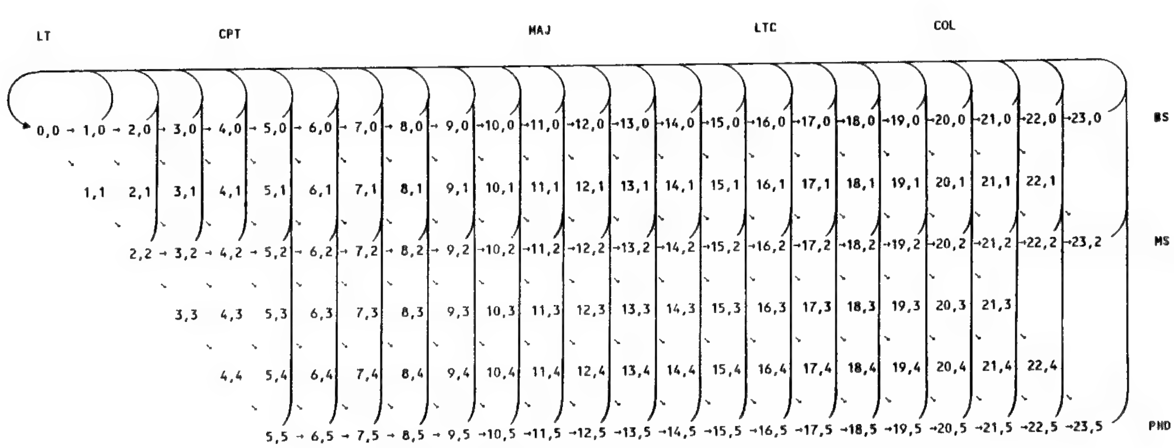


**Figure 1.** Relationship Between States for the Markov Decision Process.

officer in state $(i, 0)$, $i = 0..21$, or $(i, 2)$, $i = 2..20$, may be probabilistically chosen to enter a graduate education program. The officer's time-dependent state is a Markov process, meaning that the joint probability distribution of his future states is determined entirely by his present state and is not influenced by prior history.

In the long-run, the rate at which an officer transitions out of any state must equal the rate at which he transitions into that state from all others. Thus, given the state-dependent probabilities for attrition and graduate program entry, the steady-state probability distribution for the Markov process can be obtained by simultaneous solution of 125 balance equations (one for each state). The program entry probabilities are initially unknown, and determining the optimal values for these probabilities is an implicit goal of the analysis. If all solution probabilities are scaled by the total number of officers in the educational specialty, the solution reveals the average number of officers that should enter MS or PhD programs each year.

In addition to satisfying global balance, the optimal solution must ensure that all personnel inventory demands are met. Additional constraints can be constructed for this purpose. For three degree levels (BS, MS, PhD) and five grades (Lieutenant, Captain, Major, Lieutenant Colonel, Colonel), no more than fifteen constraints are needed. For an analysis concerned only with advanced degree requirements, all BS degree requirements can simply be set equal to zero. Nonzero solution variables for officers with BS degrees will merely reflect the inventory needed for MS program entry.

The constraints representing global balance and inventory requirements are all linear expressions. If the overall objective is the minimization of some linear cost function, then the optimal program entry flows can be obtained by solving a linear program. Assuming the "cost" of entering an officer into a PhD program is twice that of a MS program, a complete linear programming model can be formulated as follows:

## Parameters

$a_{i,d}$ = attrition probability for officer with $i$ years service and degree level $d (0 \le a_{i,d} \le 1)$

$R_{d,g}$ = requirement (number of authorized positions) for officers with degree level $d$ and grade $g$

$\gamma_d$ = inventory factor for degree level $d$ (desired ratio of inventory to authorized positions)

$$d = \begin{cases} 0 \Leftrightarrow \text{BS} \\ 1 \Leftrightarrow \text{MS} \\ 2 \Leftrightarrow \text{PhD} \end{cases}$$

$$g = \begin{cases} 2 \Leftrightarrow \text{Lieutenant (LT)} \\ 3 \Leftrightarrow \text{Captain (CPT)} \\ 4 \Leftrightarrow \text{Major (MAJ)} \\ 5 \Leftrightarrow \text{Lieutenant Colonel (LTC)} \\ 6 \Leftrightarrow \text{Colonel (COL)} \end{cases}$$

## Variables

$x_{i,k}$ = number of officers with $i$ years service and $k$ years graduate education (no new action taken), $(i, k) \in \{(0..23, 0),(1..22, 1),(2..23, 2),(3..21, 3),(4..22, 4),(5..23, 5)\}$

$x'_{i,k}$ = number of officers with $i$ years service and $k$ years graduate education (sent to school), $(i, k) \in \{(0..21, 0), (2..20, 2)\}$

## Linear Program

Minimize $\sum_{i=0..21} x'_{i,0} + 2\sum_{i=2..20} x'_{i,2}$

subject to

a. global balance

$$x_{0,0} + x'_{0,0} = \sum_{i=1..22} a_{i,0} x_{i,0} + x_{23,0} + \sum_{i=2..22} a_{i,1} x_{i,2} + x_{23,2} + \sum_{i=5..22} a_{i,2} x_{i,5} + x_{23,5}$$

$$x_{1,0} + x'_{1,0} = x_{0,0}$$

$$x_{j,0} + x'_{j,0} = (1 - a_{j-1,0}) x_{j-1,0} \qquad j = 2..21$$

$$x_{j,0} = (1 - a_{j-1,0}) x_{j-1,0} \qquad j = 22..23$$

$$x_{j,1} = x'_{j-1,0} \qquad j = 1..22$$

$$x_{2,2} + x'_{2,2} = x_{1,1}$$

$$x_{j,2} + x'_{j,2} = (1 - a_{j-1,1}) x_{j-1,2} + x_{j-1,1} \qquad j = 2..20$$

$$x_{j,2} = (1 - a_{j-1,1}) x_{j-1,2} + x_{j-1,1} \qquad j = 21..23$$

$$x_{j,3} = x'_{j-1,2} \qquad j = 3..21$$

$$x_{j,4} = x_{j-1,3} \qquad j = 4..22$$

$$x_{5,5} = x_{4,4}$$

$$x_{j,5} = (1 - a_{j-1,2})x_{j-1,5} + x_{j-1,4} \qquad j = 6..23$$

b. inventory demand

$$\sum_{i=0..3} x_{i,0} + \sum_{i=2..3} x_{i,2} \geq \sum_{d=0..2} R_{d,2}\gamma_0$$

$$\sum_{i=4..10} x_{i,0} + \sum_{i=4..10} x_{i,2} + \sum_{i=5..10} x_{i,5} \geq \sum_{d=0..2} R_{d,3}\gamma_0$$

$$\sum_{i=11..15} x_{i,0} + \sum_{i=11..15} x_{i,2} + \sum_{i=11..15} x_{i,5} \geq \sum_{d=0..2} R_{d,4}\gamma_0$$

$$\sum_{i=16..19} x_{i,0} + \sum_{i=16..19} x_{i,2} + \sum_{i=16..19} x_{i,5} \geq \sum_{d=0..2} R_{d,5}\gamma_0$$

$$\sum_{i=20.23} x_{i,0} + \sum_{i=20..23} x_{i,2} + \sum_{i=20..23} x_{i,5} \geq \sum_{d=0..2} R_{d,6}\gamma_0 \qquad \text{(BS+)}$$

$$\sum_{i=2..3} x_{i,2} \geq \sum_{d=1..2} R_{d,2}\gamma_1$$

$$\sum_{i=4..10} x_{i,2} + \sum_{i=5..10} x_{i,5} \geq \sum_{d=1..2} R_{d,3}\gamma_1$$

$$\sum_{i=11..15} x_{i,2} + \sum_{i=11..15} x_{i,5} \geq \sum_{d=1..2} R_{d,41}$$

$$\sum_{i=16..19} x_{i,2} + \sum_{i=16..19} x_{i,5} \geq \sum_{d=1..2} R_{d,5}\gamma_1$$

$$\sum_{i=20..23} x_{i,2} + \sum_{i=20..23} x_{i,5} \geq \sum_{d=1..2} R_{d,6}\gamma_1 \qquad \text{(MS+)}$$

$$\sum_{i=5..10} x_{i,5} \geq (R_{2,2} + R_{2,3})\gamma_2$$

$$\sum_{i=11..15} x_{i,5} \geq R_{2,4}\gamma_2$$

$$\sum_{i=16..19} x_{i,5} \geq R_{2,5}\gamma_2$$

$$\sum_{i=20..23} x_{i,5} \geq R_{2,6}\gamma_s \qquad \text{(PhD)}$$

c. non-negativity

$$x_{i,k}\ x'_{i,k} \geq 0\ \forall i, k$$

Note that the inventory constraints strictly enforce grade requirements, with the one exception that a PhD officer in the Captain longevity range can fill a PhD Lieutenant position (i.e., the model implicitly "corrects" any such pathological requirement). Otherwise, each grade requirement can be satisfied only by officers in the associated longevity range. The inventory factors $\gamma_d$ are included in the model so that requirements can be scaled up to reflect external factors such as assignment overlaps, career broadening assignments, resident Professional Military Education, operational assignments, etc. The model does not allow officers in graduate education programs to be counted against requirements.

The key assumptions associated with the complete Markov decision model can now be summarized as follows:

1. Officers within an academic specialty are statistically identical and behave independently.
2. The average size and distribution of the overall officer population within a specialty remains constant.
3. Future attrition probabilities are determined by current longevity and degree level.
4. All graduate programs are completed successfully (no attrition during program).
5. Grade requirements can be satisfied by educationally qualified officers with appropriate longevity.

It should be noted that the effect of an Active Duty Service Commitment (ADSC) on officer retention is not explicitly captured in the model. If supporting data were available, this effect could be modeled by adding a third dimension to the state space (number of years ADSC remaining). However, the formulation would be substantially more complex and would therefore lose some of its explanatory power. At present, the effect of the ADSC must be considered in assigning the attrition probabilities $a_{i,d}$.

## IMPLEMENTATION AND RESULTS

The model has been implemented in FORTRAN, relying on the IMSL subroutine DLPRS for solution of the linear program. Typical output for educational specialty 0YEY (Operations

Research) is presented in Figure 2. Note that the primal solution not only offers optimal flow numbers, but also the optimal composition (grade structure) of MS and PhD classes. Since no attrition is permitted during degree programs, the number of officers beginning the second year of each program is exactly equal to the number that entered the program one year earlier (e.g., $x_{i,1} = x'_{i-1,0}$, $i = 1..22$). At graduation, an optimal MS class would consist of 6 Lieutenants, 14 Captains, and $1.6 \approx 2$ Majors. This result agrees remarkably well with historical class composition, which inspires confidence in the model since 0YEY positions have remained somewhat stable despite the Air Force drawdown. The results also provide a dual solution. At optimality, each dual variable indicates the reduction in overall cost that would be realized if the corresponding requirement were reduced by one person. The constraints with nonzero dual solution variables are the binding constraints in the linear program solution.

The model can easily be adapted and extended. For example, constraints could be added to ensure that only a limited portion of MS graduates can be directly extended into PhD programs. The objective function could also be modified to allow more complex cost rules (e.g., it may "cost" more to place a more senior officer into an educational program). Different methods could also be used to enforce inventory requirement constraints. For example, the following constraint set allows any company grade officer (Captain or below) to fill any company grade position, and any field grade officer (Major or above) to fill any field grade position:

REQUIREMENTS: 0YEY

| | LT | CPT | MAJ | LTC | COL | TTL |
|---|---|---|---|---|---|---|
| BS | 0 | 0 | 0 | 0 | 0 | 0 |
| MS | 6 | 79 | 40 | 27 | 3 | 155 |
| PHD | 0 | 9 | 11 | 12 | 3 | 35 |

INVENTORY FACTOR

| | |
|---|---|
| BS | 0.0 |
| MS | 1.4 |
| PHD | 1.2 |

ATTRITION

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | BS |
| | 0.00 | 0.01 | 0.02 | 0.03 | 0.04 | 0.04 | 0.06 | 0.05 | 0.05 | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.02 | 0.04 | 0.28 | 0.25 | 0.20 | MS |
| | | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.02 | 0.00 | 0.02 | 0.02 | 0.04 | 0.02 | 0.03 | 0.02 | 0.00 | 0.03 | 0.24 | 0.35 | 0.27 | PHD |

PRIMAL SOLUTION

| LT 0 | 1 | 2 | 3 | CPT 4 | 5 | 6 | 7 | 8 | 9 | 10 | MAJ 11 | 12 | 13 | 14 | 15 | LTC 16 | 17 | 18 | 19 | COL 20 | 21 | 22 | 23 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 21.5 | 15.5 | 15.5 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 1.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | BS |
| | 6.0 | 0.0 | 14.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | | |
| | | 6.0 | 4.2 | 18.1 | 17.8 | 17.3 | 16.6 | 15.9 | 13.5 | 12.8 | 12.1 | 11.5 | 10.1 | 9.5 | 10.6 | 10.1 | 9.6 | 9.2 | 8.9 | 8.5 | 6.1 | 4.6 | 3.6 | MS |
| | | | 1.8 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.5 | 0.0 | 0.0 | 0.0 | 0.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | | | |
| | | | | 1.8 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.5 | 0.0 | 0.0 | 0.0 | 0.9 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | | |
| | | | | | 1.8 | 1.8 | 1.8 | 1.8 | 1.8 | 1.7 | 3.2 | 3.2 | 3.1 | 3.0 | 3.8 | 3.7 | 3.6 | 3.5 | 3.5 | 3.4 | 2.6 | 1.7 | 1.2 | PHD |

| | |
|---|---|
| Annual MS (m): | 21.5 |
| Annual PHD (p): | 4.2 |
| Cost (m+2p): | 29.9 |

DUAL SOLUTION

| | LT | CPT | MAJ | LTC | COL |
|---|---|---|---|---|---|
| BS | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| MS | 0.01 | 0.04 | 0.05 | 0.27 | 0.00 |
| PHD | 0.00 | 0.01 | 0.00 | 0.51 | 0.00 |

THIS SOLUTION STRICTLY ENFORCES GRADE REQUIREMENTS

**Figure 2.** Results for Specialty Code 0YEY (Operations Research).

$$\sum_{i=0..10} x_{i,0} + \sum_{i=2..10} x_{i,2} + \sum_{i=5..10} x_{i,5} \geq \sum_{d=0..2} \sum_{g=2..3} R_{d,g}\gamma_0$$

$$\sum_{i=11..23} x_{i,0} + \sum_{i=11..23} x_{i,2} + \sum_{i=11..23} x_{i,5} \geq \sum_{d=0..2} \sum_{g=4..6} R_{d,g}\gamma_0 \qquad \text{(BS+)}$$

$$\sum_{i=2..10} x_{i,2} + \sum_{i=5..10} x_{i,5} \geq \sum_{d=1..2} \sum_{g=2..3} R_{d,g}\gamma_1$$

$$\sum_{i=11..23} x_{i,2} + \sum_{i=11..23} x_{i,5} \geq \sum_{d=1..2} \sum_{g=4..6} R_{d,g}\gamma_1 \qquad \text{(MS+)}$$

$$\sum_{i=5..10} x_{i,5} \geq \sum_{g=2..3} R_{2,g}\gamma_2$$

$$\sum_{i=11..23} x_{i,5} \geq \sum_{g=4..6} R_{2,g}\gamma_2 \qquad \text{(PhD)}$$

This formulation permits greater flexibility in satisfying grade requirements.

Table 1 summarizes typical model results for all programs offered by the AFIT graduate schools. These results are based on attrition data provided by the Air Force Personnel Center and inventory factors of $\gamma_1=1.4$ and $\gamma_2=1.2$ for MS and PhD degrees respectively. All grade requirements are strictly enforced. For each specialty, the table shows total MS requirements $R_1 = \Sigma_{g=2..6} R_{1,g}$ (with corresponding annual flow $m = \Sigma_{i=0..21} x'_{i,0}$) and total PhD requirements $R_2 = \Sigma_{g=3..6} R_{2,g}$ (with corresponding annual flow $p = \Sigma_{i=2..20} x'_{i,2}$). The annual flow numbers should be considered minimum values since they assume that all ed-

**Table 1.** Advanced Degree Requirements and Annual Flows.

| Code | Specialty | $R_1$ | $m$ (MS flow) | $R_2$ | $p$ (PhD flow) |
|---|---|---|---|---|---|
| 0Cxx | Computer Technology | 286 | 45.5 | 28 | 3.0 |
| 0YEY | Operations Research | 155 | 21.5 | 35 | 4.2 |
| 0YRY | Space Operations | 60 | 9.7 | 0 | 0.0 |
| 0YSY | Operational Analysis | 70 | 10.5 | 2 | 0.5 |
| 1AGE | Environmental & Eng Management | 146 | 23.2 | 8 | 1.0 |
| 4Axx | Aeronautical Engineering | 131 | 32.0 | 60 | 7.5 |
| 4Bxx | Aerospace Engineering | 19 | 2.5 | 5 | 0.6 |
| 4Exx | Astronautical Engineering | 80 | 13.5 | 16 | 1.6 |
| 4Ixx | Electrical Engineering | 477 | 77.5 | 113 | 12.5 |
| 4Mxx | Mechanical Engineering | 60 | 13.5 | 21 | 3.0 |
| 4Qxx | Nuclear Engineering | 45 | 6.6 | 12 | 1.2 |
| 4Txx | Systems Engineering | 66 | 7.8 | 2 | 0.4 |
| 4Wxx | Computer Engineering | 44 | 10.7 | 11 | 1.6 |
| 8Fxx | Meteorology | 244 | 40.9 | 20 | 2.2 |
| 8Hxx | Physics | 109 | 20.2 | 76 | 6.9 |
| 1AMH | Contracting Management | 68 | 8.9 | 0 | 0.0 |
| 1ASY | Systems Management | 118 | 14.1 | 2 | 0.4 |
| 1APY | R&D Management | 28 | 4.4 | 4 | 0.7 |
| 1ASA | Cost Analysis | 80 | 10.6 | 4 | 0.8 |
| 1ASM | Software Systems Management | 19 | 3.6 | 1 | 0.3 |
| 1AMJ | Acquisition Logistics Management | 37 | 5.5 | 0 | 0.0 |
| 1AMM | Maintenance Management | 4 | 0.9 | 0 | 0.0 |
| 1AMS | Supply Management | 20 | 3.9 | 1 | 0.2 |
| 1AMY | Logistics Management | 118 | 16.7 | 4 | 0.7 |
| 1ATY | Transportation Management | 77 | 8.7 | 1 | 0.3 |
| 1AUY | Information Resource Management | 93 | 13.0 | 0 | 0.0 |

ucational programs are successfully completed and that all officers receive their advanced degrees at optimal career longevity.

Many important insights can be obtained from the model results. For example, Table 1 indicates that while the total MS requirement for Aeronautical Engineering (131) is less than that of Operations Research (155), the annual demand for graduates is significantly higher. This phenomena occurs primarily because the vast majority of Aeronautical Engineering positions require company grade officers (Lieutenants and Captains). Relatively large numbers of officers must receive MS degrees early in their careers to fill these positions, and many of them are essentially lost from the usable inventory upon promotion to Major. This example illustrates the hazards of a simple comparison between inventory and requirements without regard to grade constraints. The model presented in this article can explicitly address this type of issue.

## CONCLUDING REMARKS

The value of the Markov decision model has been demonstrated through its successful application in a major re-engineering study at the Air Force Institute of Technology. The study was performed by a carefully selected Process Action Group, comprised of six senior faculty and administrators. The Group employed educational quota predictions based on model results for several scenarios to recommend a future size and composition of the AFIT personnel structure [11]. A specific plan to phase-out 42 of the 214 positions in the two graduate schools was formulated and is now under implementation. The first phase, which removes 30 positions, is near completion. Immediate annual cost savings of $2.4 million are expected; this value will increase to $3.2 million with full implementation. A recent report by the AFIT Board of Visitors, chaired by a retired four-star General, included the observation that "AFIT leadership has done a thorough, systematic assessment of faculty and staff needs to accomplish their Air Force mission" [1].

The situation faced by AFIT and the Air Force may be similar to that of many other organizations. Expensive and lengthy specialized training is required by many military career fields that are affected by grade structure constraints. Examples might include air traffic control, special forces, aircrew, naval vessel duty, and intelligence. Furthermore, the current industrial environment is increasingly characterized by corporate downsizing, restructuring, and workforce cross-training. Many commercial and public entities incur substantial costs for training and education of personnel to attain their objectives. The general approach and specific model described in this article may be useful to such institutions in improving their organizational structures and educational policies.

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# About our Authors

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## FINDING AN OPTIMAL STATIONING POLICY FOR THE US ARMY IN EUROPE AFTER THE FORCE DRAWDOWN

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# Editorial Policy and Submission of Papers

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Gregory S. Parnell, Editor, *Military Operations Research*

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The editorial policy has changed. We have developed procedures and instructions to authors that will expedite the review and publication process.

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The articles submitted to the journal cover many military operations research problem domains and methodologies. In order to assign the most appropriate reviewer, we have identified application areas and methodologies. We have also expanded the number of Associate Editors to insure we have expertise in all of these areas. In addition, we have developed procedures to insure timely review of submitted papers. To help expedite the publication process, we have developed instructions for *Military Operations Research* authors (see below).

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| |
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